Stratus Consulting

Economic Value of Current and Improved Weather Forecasts in the U.S. Household Sector

Prepared for:

Dr. Rodney Weiher
Chief Economist
Office of Policy and Strategic Planning
with the financial support of the
NPOESS, National Environmental Satellite Data and Information Service
National Oceanic and Atmospheric Administration

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EXECUTIVE SUMMARY

The National Weather Service (NWS) within the National Oceanic and Atmospheric Administration (NOAA) is the primary federal agency responsible for the collection, analysis, and dissemination of weather forecast information. With an annual budget of about $1,383 million, the average U.S. household pays about $13 a year for the services of the NWS. There is little if any reliable economic information indicating whether these services are worth this $13 a year to households, although it is widely assumed that the benefits far exceed the costs. Furthermore, there is even less information on the value to households of potential improvements to or changes in current weather forecasting services. As NOAA considers new programs and implements new technologies, it is likely to be asked to justify proposed new expenditures using a benefit-cost framework.

This study was commissioned to assist in evaluating and quantifying, to the extent possible, the benefits to households of potential improvements in weather forecasting services, as well as how the public values current forecast services. Table S-1 presents this study's best estimates of annual per household values for improved and current weather forecasts. Based on Census estimates of about 105 million U.S. households, total national values for improving weather forecasts to the maximum levels proposed in the survey are estimated to be $1.73 billion per year. We also calculate an annual national value of $11.4 billion for current weather forecast services (which includes the value of all weather forecast information services from public and private sectors).

Table S-1
Best Estimate Values for Improved and Current Weather Forecast Services ($2001)

Value	Annual Value Per Household	Total National Value [a]
Value for Improving all Forecast Attributes to their Maximum Level (as described in Table S-2)	$16	$1.73 billion
Value for Current Weather Forecast Services [b]	$109	$11.4 billion

a. Based on there being approximately 105 million U.S. households (U.S. Census, 2000).
b. This aggregation takes the median value ($109) as representative of household values for current forecast services.

S.1 PURPOSE

This study assesses methods for eliciting households' values for improved weather forecasting services. We focus on households because they are most likely the largest end user of the weather forecast services provided by the NWS. Households are also the relevant unit for benefit-cost analysis of potential improvements for weather services. As a first step, we focus primarily on household values for potential improvements in "day-to-day" weather forecasts. With most households probably using day-to-day weather forecasts at least once a day and about 105 million households in the United States, the total value of improving day-to-day weather forecasts may be enormous even if the per household value is relatively small.

Because weather forecasts have some of the properties of public goods (nonrival and potentially nonexcludable), markets have not developed for the provision of weather forecasts for the general public. There is thus little or no market data on households' values for weather information. To elicit these values we developed a survey instrument through a series of focus groups, one-on-one interviews, a pilot study in Denver, and external review by survey research experts. Data collection was implemented by individual self-administered surveys conducted at survey centers in nine cities across the United States in October 2002 with a total of 381 participants.

Input on technical aspects of potential weather forecasting improvements was provided by Atmospheric Science Advisors, LLC (ASA). Four attributes of weather forecasts were considered in the survey: the frequency of forecast updates, the accuracy of one-day forecasts, the accuracy of multiday forecasts, and the geographic detail of forecasts. Table S-2 shows the baseline levels of these forecast attributes and levels of potential improvements considered by respondents.

Table S-2
Attribute Levels for Storm Survey

Attribute Level	Frequency of Updates (times per day)	Accuracy of One-Day Forecasts	Accuracy of Multiday Forecasts	Geographic Detail
Baseline	4	80%	5 days	30 miles
Minimal Improvement	6	85%	7 days	15 miles
Medium Improvement	9	90%	10 days	7 miles
Maximum Improvement	12	95%	14 days	3 miles

S.2 METHODS

The survey uses three different stated preference nonmarket valuation approaches to elicit household values for current or improved weather forecasting services. Stated preference valuation includes stated choice methods (similar to conjoint analysis used in marketing research) and stated willingness-to-pay (WTP) methods.

First, we use stated choice methods to examine values for potential changes in attributes of day-to-day weather forecast information: frequency of updates, accuracy of one-day forecasts, accuracy of multiday forecasts, and geographic detail (resolution).

Second, we ask individuals their WTP for a specific program that would improve weather forecast attributes. The improvement in forecast attributes was varied across the 20 versions of the survey. Several followup questions to the WTP questions help assess the reliability and validity of the value statements.

Third, we ask individuals if the current weather forecast services were worth what they were currently paying in taxes for these services. By varying the amount individuals were told they currently paid, this question is similar to a referendum WTP question.

S.3 RESULTS

Analysis of the stated choice questions indicates that improving the accuracy of one-day forecasts is valued most, followed by improving the accuracy of multiday forecasts and geographic detail. Overall, individuals appear to have little value for increasing the frequency of weather forecast updates. While this holds for the day-to-day forecasts examined in this study, the frequency of updates may be very crucial in situations such as severe weather (e.g., tornadoes or floods), which was not addressed. Using the values estimated for changes in the attribute levels, we calculate individuals' value for a program which would increase all attributes to their maximum level between $12 and $17 a year per household with a best estimate of $16.

Analysis of the valuation responses indicates that, as expected, values for improving weather forecasts are related to sociodemographic characteristics such as income and education, how much time an individual spends outdoors on the job, and how individuals use weather information in making behavioral decisions (such as what to do on the weekend). It is also found that individuals' WTP statements may be influenced by how they view the scenario presented to them for valuation. Some respondents state low values for the program, not because they have low value for improved weather information, but because they may doubt some aspect of the scenario, such as the likelihood that their money would actually go to the program. The average WTP for the "maximum" improvement in weather forecasting program ranges from $12 to $13 a year per household depending on how we treat individuals answers to the followup questions. These values are in the same range as those derived from the stated choice valuation questions.

The third valuation question asked individuals if the services they *currently* receive from the NWS are worth what they currently pay in taxes for these services. By varying the amount indicated as the current cost to taxpayers, we examine how willingness to pay for current services varies. With current costs to taxpayers of about $13 a year per household for federal forecasting services, there would appear to be significant excess benefits generated by current weather service activities. More than 86% of individuals indicate they are willing to pay at least $10 for current services and 80% value current forecasts at at least $32. Given the format of the question, this per household value includes all current forecast information, including that for normal weather, severe weather, aviation, and marine forecasts. It should also be noted that individuals probably do not decompose their values for weather forecasts into benefits provided by the public sector versus value added provided by the private sector. Taking a conservative approach we would therefore take individuals' values as being values for the final product of weather forecasts as households receive them. We estimate a median household value of about $109 a year for current weather forecast services.

The survey also elicited information on what characteristics are most useful to individuals in weather forecasts and current observations. As in prior studies, we found that precipitation and temperature are the most important characteristics of weather forecasts and of current weather observations. Some weather information characteristics (such as dewpoint or barometric pressure) are infrequently used and may be poorly understood by the general public. Further research would be necessary to determine if these potentially poorly understood characteristics have important effects on individuals' use of or value for weather information.

Statistical analysis of subjects' responses indicates that there are differences between individuals in how important certain characteristics of weather forecast information are. For instance, wind strength and amount of precipitation was more important to those who work outside more, and chance of and amount of precipitation, extent of cloud cover, low temperature, and how windy it will be were all more important to those whose spend more leisure time outside.

Differences also exist between individuals in their use of weather forecast information for planning social, recreational, and work activities depending on how much leisure or work time is spent outside. Differences between individuals in their use of weather forecasts lead to differences in values for improvements in weather forecasts.

S.4 RECOMMENDATIONS

The current work provides estimates of the public's value for improving weather forecasting services that can be useful to policy makers as well as in benefit-cost analysis of NWS programs. Future work may provide additional insight into individuals' uses, perceptions, and values of weather forecasts. For instance, it may be beneficial to implement the survey during different seasons since individuals' values for improved weather information may vary throughout the year.

Potential improvements in other NWS services may also generate significant benefits to households beyond the day-to-day forecasts considered in this study. Useful benefit assessments could also be undertaken for improvements for severe weather forecasts and warnings, river stage forecasts, large-scale weather systems, and seasonal to interannual forecasts.

Although this work focuses on the use of stated preference methods, approaches should be explored to derive values for weather information using revealed preference information. Significant resources are devoted to television, radio, and newspaper weather forecasts provided to the general public. While much of this information is most likely proprietary to the provider for marketing reasons, methods may be developed to confidentially obtain and analyze this information. Revealed preference data would provide support for values obtained using stated preference methods. Revealed preference valuation could provide important information on values for current weather forecast services, but may be of less help in valuing improvements in weather forecast information.

CHAPTER 1
INTRODUCTION

1.1 PURPOSE OF THE STUDY

The National Weather Service (NWS) directly and indirectly provides the nation with the most complete, accurate, and timely meteorological and hydrological information services possible within existing scientific, technological, and economic constraints.[1] The NWS, like other federal agencies, must continue to evaluate the usefulness and cost-effectiveness of the services it provides to the public. Although the value of weather information in emergencies and for agricultural and industrial uses is well established, weather information is also clearly valuable to the household sector for meeting travel, recreation, and other planning and information needs.

Unfortunately, little or no recent public information exists about the current use and value of NWS information in routine decisions made by households. For example, in a benefit-cost evaluation of the recent modernization of the NWS (Chapman, 1992), the information cited on household values for weather data was from 1981.

Among the issues of interest to the NWS is the use of and value for current forecasts and, particularly, potential improvements in forecasts. Furthermore, the NWS would like to evaluate potential demand for new services before investing resources in developing those services. Some delivery technologies for weather information have changed dramatically since the 1970s and early 1980s, and future information delivery technologies promise to be even more innovative. Changes in these technologies might alter household demand for weather information. Which service characteristics are the most beneficial to households? What improvements in services are most highly valued by households? We begin to address these issues in this study.

In looking at the demand for weather information used by households, several key household demand issues are addressed, including:

1. Throughout this report we refer to the services and activities of the NWS, yet include the different services throughout the National Oceanic and Atmospheric Administration (NOAA) that provide meteorological information and research (e.g., NESDIS, the National Environmental Satellite, Data, and Information Service). We focus on the NWS for three reasons. First, individuals are unlikely to be aware of distinctions between different services within NOAA. Second, values elicited for improved weather forecasts are likely to be independent of which service within NOAA is ultimately responsible for developing or implementing improvements in weather forecasting services. And third, as determined through survey pretesting, individuals are reasonably aware of the NWS and the services it provides and therefore we discuss the NWS in the survey instrument used in this study. Thus, while we primarily discuss the NWS, we feel the results of this work provide useful information for any weather related activity within NOAA that supports one or more of the examined improvements in day-to-day forecasts.

- identifying the weather information needs of different household users and the perceived importance and quality of this information

- identifying the characteristics of different household users and how they use weather information, including NWS information

- assessing the demand for changes in the characteristics of NWS information such as increased frequency, increased geographic detail (resolution), accuracy of one-day forecasts, and accuracy of multiday forecasts

- estimating the value of current weather forecast information services provided by the NWS to the household sector.

The current research is an important step in understanding these issues in a systematic manner. To our knowledge, the current survey administered in this study is the first to attempt to elicit economically valid and reliable estimates of households' willingness to pay for improved weather forecasting.[2]

The results of this research indicate that the survey successfully elicits information about households' perceptions and uses of and values for improved weather forecast information. This information includes how different attributes of weather forecast information are valued by households as well as how values vary depending on individuals' uses of weather information and socioeconomic characteristics.

1.2 OVERVIEW

In this study to elicit household values for weather forecasting services, the primary focus is on households' values for improved weather forecasts under normal or day-to-day weather conditions. In other work we are beginning to examine methods for eliciting individuals' preferences for improved forecasts for severe weather (i.e., hurricane forecasting). Information is also elicited on individuals' values for the current weather forecast system. We focus on households as the largest end user of the weather forecast services. With most households using day-to-day weather forecasts daily and about 105 million households in the United States,[3] the total value of improving day-to-day weather forecasts may be enormous even if the per household value is relatively small.

2. Macauley (1997) states that "to date, CV [contingent valuation] has not been applied to study the value of weather information." While we review two studies that elicit values for weather information, these studies focus on current weather information rather than improved. Another study of the value for improved weather information did use a CV type question but is subject to question regarding the validity and reliability of the manner in which the method was implemented (Prototype Regional Observing and Forecasting Service, 1979).

3. 104,705,000 households as of March 2000. Source: U.S. Census, 2000.

The study uses “stated preference methods” to examine values for four attributes of weather information: frequency of updates, accuracy of one-day forecasts, accuracy of multiday forecasts, and geographic detail (resolution). Stated preference methods are used in economic benefit estimation when markets do not exist for the goods or services being valued. In this case there is little or no market information on households’ value for weather forecast information. Nonmarket valuation methods used in the survey include stated choice (SC) questions and stated value (SV) questions — state-of-the-art nonmarket valuation techniques.[4]

The survey also obtains data on households’ sources of, perceptions of, and uses of weather information. While the current study focused mainly on weather information under “normal” or “day-to-day” weather conditions, the survey begins to explore perceptions and uses of weather information related to severe weather conditions.

The study elicited values from individuals in nine different cities in focus groups settings. The cities were chosen one each from the nine regions defined by the National Climate Data Center for climate summaries (Figure 1-1). The cities were San Diego (California), Portland (Oregon), Denver (Colorado), Billings (Montana), Oklahoma City (Oklahoma), Madison (Wisconsin), Columbus (Ohio), Albany (New York), and Miami (Florida).

Historical data on weather forecasts and observed weather conditions were used to create indices of weather variability and forecast accuracy for each city. These indices were used to explore how individuals’ perceptions of and values for improved forecasts and current forecast services relate to local weather variability (e.g., persistence) and the quality of forecasts currently available to the respondents.

1.3 REPORT STRUCTURE

Chapter 2 of this report discusses the economic value of weather information, including a general discussion of the value of information, an introduction to nonmarket valuation issues relevant to this study, and reviews of empirical studies of households’ perceptions of and values for weather information. Chapter 3 discusses survey development, design, pretesting, and implementation. Chapter 4 presents results on uses and perceptions of day-to-day weather forecasts and on severe forecast information. Chapter 5 presents results of the valuation analysis for improved forecasts and current weather forecasts. Chapter 6 provides our conclusions and outlines recommendations for further research. The appendices include a copy of the survey instrument, statistical results, and technical information on the analysis.

4. We use the term stated value (SV) to indicate value elicitation through direct willingness-to-pay (WTP) or willingness-to-accept (WTA) questions. While the literature has generally referred to such methods as contingent valuation methods (CVMs), we use the SV term to differentiate SV from stated choice questions. Stated choice includes referendum type questions that have often also been considered CVM questions.

Figure 1-1
NCDC Climate Regions

CHAPTER 2
VALUATION OF WEATHER FORECAST INFORMATION

2.1 INTRODUCTION

One approach to improving weather forecasts would be to devote resources to improving forecasts as determined by some technical measure of forecast accuracy. While this approach certainly represents the *potential* for increased value, it is important to note that there is no direct relationship between technical measures of forecast quality and households' values for forecasts. Instead, it is necessary to understand the complete process of translating changes in forecast accuracy into values. Hooke and Pielke (2000) present a simple model of this process. They identify three subprocesses in a simple model of the weather prediction "system."

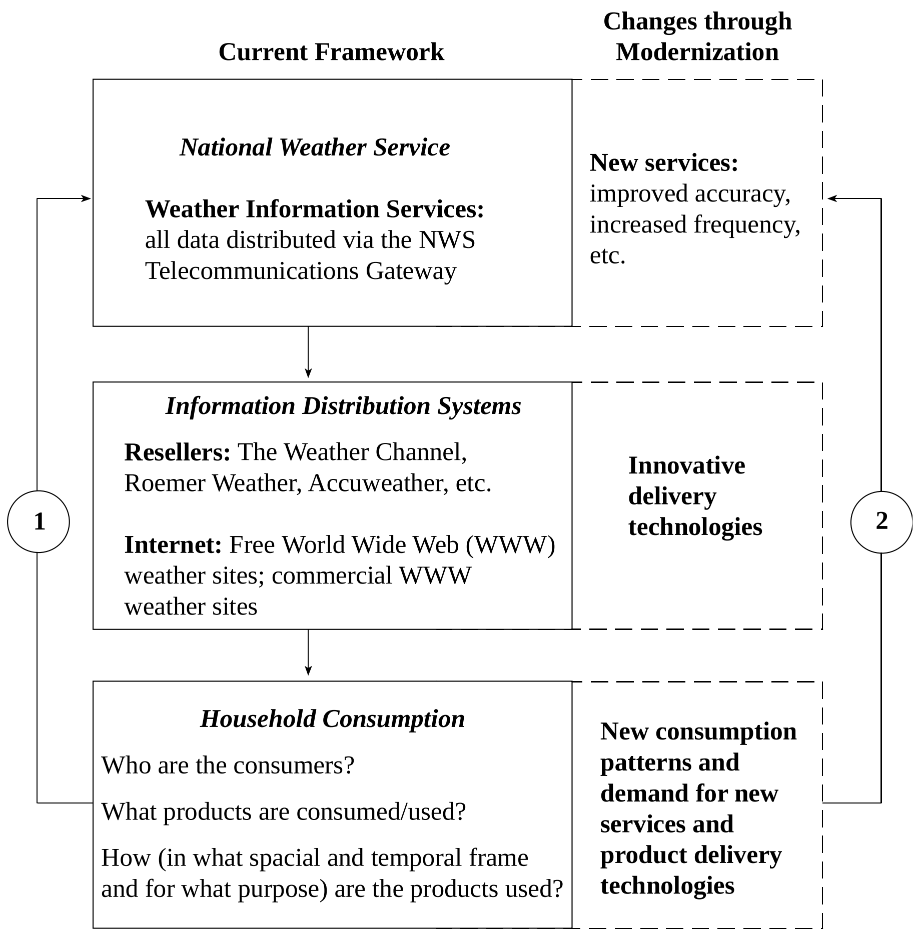
predict ⇒ communicate ⇒ use

Each subprocess must be understood in order to understand the relationship between changes in weather forecast information and the value of these changes. An expanded version of this model, Figure 2-1, shows that "predict" involves the process of data collection, analysis, and forecasting. Communication to households can take place either directly from the NWS or through resellers or other information distribution. Household use is a multidimensional combination of heterogeneous households using weather information for different activities. The process of "use," broadly defined, generates value through household decision-making. Arrows 1 and 2 in Figure 2-1, from households back to the NWS, indicate information on households' value for the services and products generated by the NWS. This information may be used by the NWS to improve or adjust current products and services (the arrow labeled 1) or to develop and implement new products and services (the arrow labeled 2).

To elicit economically valid and reliable household values for improved or current weather services, each of these subprocesses must be considered. Information on current attributes of weather forecasts and potential improvements in weather forecasts must be based on information from the "predict" portion of the forecast process. While not the primary focus of this research, an understanding of the communication process is necessary to convey information to individuals on potential changes in forecast services. It is also useful to understand how individuals perceive and use forecast information in order to properly interpret and elicit values for these services.

To provide background and a theoretical foundation for the work reported in the study, this chapter reviews theoretical issues behind the concept of "the value of information" (Section 2.2) and nonmarket valuation methods (Section 2.3). These sections provide the foundation for the values elicited in the study and the methods used to elicit them. We then review previous studies

Figure 2-1
Linkages between Three Components of Knowledge Baseline, including Potential Modernization Influences



of individuals' perceptions of and uses of weather forecast information (Section 2.4) and previous empirical work to elicit households' values for current or improved weather information services (Section 2.5).

2.2 VALUE OF INFORMATION

Future weather inherently involves risk and uncertainty, concepts that have been addressed in many forms in economic theory and modeling. Weather forecasts comprise information about future events, which may or may not be of use to individuals or groups in dealing with the risk and uncertainty of future weather conditions. While weather outcomes have real impacts on behavior and economic consequences, information about potential weather outcomes may also have value. We focus here on the *value* of information in dealing with risk and uncertainty of future weather outcomes.

Phlips (1988) makes a distinction between uncertainty and asymmetrical information. Asymmetrical information involves parties to a transaction having different information and thus having the opportunity to gain from behaving strategically. While it is possible to construe situations where some parties may have better or different weather information than others, the primary focus of this research relates to how individuals respond to risk and uncertainty about future weather conditions.[1]

A further distinction is usually made between risk and uncertainty. Uncertainty entails situations in which potential outcomes are either unknown in advance or probabilities of those outcomes are unknown. With respect to weather information, most individuals probably have some concept of potential future weather outcomes based on past experience. With respect to the probability of those outcomes, it is often assumed that individuals have prior beliefs about the distribution of those outcomes. Individuals may have beliefs based on prior experience or they may have some belief that the weather tomorrow will not be too different from today's. Regardless of the source or validity of prior beliefs about the potential outcomes and distribution of those outcomes, individuals' behavior with respect to future weather conditions is often modeled as behavior in the face of risk rather than uncertainty.

The value of information then relates to how individuals, or "economic agents," can or will react to changes in the information available when they face a "weather risk." There are several approaches for modeling decision making and the value of weather information. The most common approach has been to model decision making at the firm level based on profit maximization or loss minimization (Suchman et al., 1981; Mjelde et al., 1989). Value of information can also be modeled at the individual level. Hilton (1981) is often cited in the weather information literature for identifying factors determining the value of weather information to the individual decision maker in a utility-theoretic framework (Mjelde et al., 1989; Murphy, 1993; Johnson and Holt, 1997).

2.2.1 Theoretical Model of the Value of Information

We discuss Hilton's (1981) model to indicate the welfare-theoretic basis of measures of the value of improved weather information. Other theoretical discussions of the value of information are discussed as an indication of the complexity of the issue of valuing improvements in

1. Phlips (1988) also raises the issue of cognitive dissonance, which may affect how individuals respond to changes in information that are not captured in a model as described here. This could relate to important and interesting issues with respect to how weather information is communicated and then how individuals incorporate this information, react to it, and ultimately value it.

information. Having some understanding of the range of these issues is important in understanding approaches to eliciting individuals' values for improved weather information.

Hilton (1981) identifies three formulations of the value of information: (1) utility, (2) willingness to pay (WTP), and (3) willingness to accept (WTA). Each has a basis in welfare economics related to exact measures of welfare change (see Freeman, 1993). Consistent with the values elicited in the current survey, we focus on the WTP formulation. Hilton (1981, p. 58) defines WTP as the value *F(h)* that satisfies the equation:

$$\int_{y_h \in Y_h} \max_{x \in X} \int_{s \in S} u\left[w(x,s) - F(h)\right] p(s|y_h)\, p(y_h) = \max_{x \in X} \int_{s \in S} u\left[w(x,s)\right] p(s)$$

where

h	= information system h
$\{y_h\} \in Y_h$	= set of signals for system h
S	= set of uncertain states of nature
X	= set of actions
w	= outcome function mapping act-state pairs into outcomes, $z \in Z$ [i.e., $z = w(x,s)$]
u	= utility function mapping outcomes into utility levels
$p(s)$	= prior probability distributions over states
$p(s\|y_h)$	= posterior distribution over states given signal y_h from information system h
$p(y_h)$	= prior distribution over signals from system h
$\int$	= general summation operator valid for either a continuous or discrete set.

The right-hand side of the equation indicates the behavioral decision the individual makes, *x*, given some prior beliefs about future states of the world, *s*. This terms represents the individual's expected utility given the prior probability distribution over states. The term *w(x,s)* identifies the outcomes of this behavioral decision given different states of the world, *s*, and *u[w(x,s)]* indicates the utility given those outcomes, behavioral decisions, and states of the world.

In this WTP formulation, the left-hand side of the equation includes the demand value, *F(h)*, of the information system, *h*. *F(h)* represents the maximum WTP for the information system, *h*, that will leave the individual at least as well off as not having the information.[2] The term $p(s|y_h)$ allows for a Bayesian framework of updating prior beliefs with the new information. Within this formulation, four determinants of the value of the information system, *F(h)*, are implicit:

2. Using a similar modeling approach, Macauley (1997) shows specifically that the individual will value information up the point where the marginal benefit equals the marginal cost of additional information.

- the structure of the action set or potential behavioral responses, x
- the structure of the "payoff function" $u(w(x,s))$
- degree of uncertainty in the prior, $p(s)$
- the decision maker's perception of the mapping from the uncertain states of nature, s, into the signals from the information system, $p(s|y_h)$.

It is important to note that the value of the information system will depend on the form of the utility function, $u[w(x,s)]$, and not just the outcomes, $w(x,s)$.[3] Several prescriptive studies of the value of weather information are based on the outcomes and do not recognize the importance of the utility function. It is also worth noting that, depending on the form of the utility function, the individual may make no different behavioral decisions with the new information system yet could still be better off. This could occur under conditions of risk aversion if the information system reduces uncertainty.[4]

Similar factors are discussed in Davis and Nnaji (1982), although they also discuss the cost of information as a determinant. The difference in approaches relates to Hilton identifying the individual's total value of the information and Davis and Nnaji identifying net value.

Also implicit in this formulation is that the value of the information system is based on ex ante measures of value. Once the outcome is known, ex post, there is no uncertainty and the (rational) individual is unwilling to pay for the information. Several authors have examined the correct welfare measure under demand or price uncertainty. Anderson (1979) derives theoretical welfare measures under conditions of demand (taste and preference), price, and income uncertainty. Anderson describes the ex ante compensating variation (ACV) measure as the appropriate measure for benefit-cost analysis. Choi and Johnson (1987) discuss the relationship between ex ante equivalent variation, which is a theoretically correct welfare measure, and expected equivalent variation, which is operationally observable, under price uncertainty. Choi and Johnson suggest that application of ex ante equivalent or compensating variation requires information on risk attitudes, which makes them unlikely to be used empirically. They do conclude though that "where income risk aversion is assumed, expected equivalent variation provides a lower bound for ex ante equivalent variation" (p. 411).

Gould (1974), Hilton (1981), and Hess (1982) have used similar approaches to examine the relationship between the characteristics of information systems and their value. These studies discuss relationships between information systems and the value of information, finding the following:

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3. "Usually expected value is represented by a utility function, about which different assumptions can be made as to its functional form, which in turn can proxy the individual's attitude towards risk (he can be a risk lover, or be risk averse, or be risk neutral)" (Macauley, 1997. p. 3).

4. "Ideally, the user's attitude toward risk should be investigated and then taken into account in all forecast-value studies" (Murphy, 1994, p. 10).

- There is no general monotonic relationship between absolute or relative risk aversion and the value of information.
- There is no general monotonic relationship between wealth and the value of information.
- There is no general monotonic relationship between information value and the Rothschild-Stiglitz measure of the degree of uncertainty.[5]
- It is not universally true that the value of information is increasing in the number of nonzero probabilities.
- It is not universally true that the value of information decreases universally as the probabilities concentrate more on a single value.
- It is not universally true that the value of information decreases universally as it is easier to forecast the outcome.
- It is not universally true that increases in the variance of the outcomes necessarily increase the value of information.

Gould (1974, p. 83) concludes that "resources devoted to information gathering may not be concentrated in those areas where uncertainty is greatest . . . because the payoff function from gathering information is itself a function of uncertainty, and risk aversion applies to the decision to acquire information as it does to other decisions" and that "individuals may exhibit preference for what 'objectively' appears to be riskier activities even though they are risk averse" if the cost of information is related to its value.

Several aspects of these findings are relevant to empirical efforts to elicit values for improved weather forecast information.

First, efforts to elicit values for improved weather information must allow for potential risk aversion. In the current study, by asking individuals stated preferences for such information, we are not imposing a "structure" on their preference that precludes risk aversion. In other words, if individuals are risk averse, this is implicit in the values elicited in the study.

Second, it is useful to have a better understanding of how individuals perceive the information they are receiving and whether they have the flexibility to use this information. By eliciting information on individuals' perceptions and uses of weather information, we can better understand whether their stated values are consistent with their perceptions and uses of weather information.

5. See Rothschild and Stiglitz, 1970 and 1971.

Third, fully modeling and empirically estimating the relationships between information characteristics and individuals' value is a complex, multidimensional exercise. We do not claim to have fully explored all aspects of these relationships. As is often the case in the gap between theory and application, we have only empirically addressed a limited number of the issues that theory suggests may be relevant in understanding the value of improved weather information. Nevertheless, we do feel that this study elicits values that are consistent with the theoretical basis of welfare measurement.

2.3 NONMARKET VALUATION

Many authors discuss weather forecasts as public goods (e.g., Anaman and Lellyett, 1996; Johnson and Holt, 1997, Freebairn and Zillman, no date-a and no date-b). Public goods are goods or services that are nonrival and nonexcludable. Nonrival means that one person's consumption of the good does not diminish others' ability to consume the good (e.g., one person knowing the weather forecast does not diminish anyone else's ability to derive a benefit from knowing the forecast).[6] Nonexcludable means that once the good is provided no one can be excluded from using the good. Weather forecasts are excludable and it is this characteristic that provides the basis for private weather forecasting services. Weather forecasts are thus better defined as quasi-public goods because of the potential for exclusion. Because the NWS has not excluded the public from the services it provides, weather forecasts have been provided as a free good.[7]

Given the quasi-public goods nature of weather forecasts, the economic value of most weather forecasting services is not directly observed in the market. It is therefore difficult to determine the economic value of the changes in these services that are provided as a result of NWS programs to improve weather forecasting, but this is exactly what is required in benefit-cost analyses. Depending on the property rights inherent in the policy problem, these values are either the maximum WTP for the good or minimum compensation that they would be WTA for forgoing the good. In the case of weather forecast improvements, WTP is identified formally as the *compensating variation* measure of welfare change, while WTA in this case is identified as the *equivalent variation* measure. For weather forecast decrements, these associations are reversed.[8]

6. "Nonrivalry also often characterizes the benefits from . . . weather monitoring stations . . ." (Cornes and Sandler, 1996, p. 8).

7. The potential for gain from exclusion has been the focus of private weather services' contention that the NWS should be privatized (Smith, 1995; Rosenfeld, 2000a).

8. For a more detailed treatment of these issues, see Just et al. (1982) and Freeman (1993).

Focusing on WTP, true value is the maximum amount the individual is willing to pay to ensure that a welfare-increasing activity takes place or to prevent a welfare-decreasing activity from being implemented.[9] For market goods, such values can often be derived from analysis of market transactions. Since certain public goods are provided at the expense of private goods or other public goods, measures of WTP for public goods and quasi-public goods are important for determining the appropriate provision of public goods and are appropriate for use in the benefit-cost context.

There are two basic approaches that economists use to estimate the economic value of nonmarket goods: revealed preference methods (RP) and stated preference (SP) methods. Revealed preference methods are applied to actual behavior and market transactions that may reveal the values implicitly placed on a nonmarket good in the context of choices made regarding market goods. Such methods include travel cost models and hedonic price models (see Freeman, 1993).

In stated preference studies, value is estimated using surveys in which a representative sample of the relevant population expresses a stated preference that can be directly or indirectly used to determine willingness to pay for a good or service. The value obtained for the good or service is contingent on the nature of the constructed market described in the survey scenario. Stated preference methods include stated value methods (SV) and stated choice (SC) methods, both of which are used in the study.

2.3.1 Stated Value Method

Stated value (SV) refers to the use of a hypothetical transaction framework in which subjects are directly asked to give information about their values for specific goods or services. SV is often defined to include direct open-ended questions such as "How much would you be willing to pay for . . . ?"

The reliability and validity of SV methods depend on the extent to which they measure true values. Some economists are skeptical because they believe that the actual exchange of dollars for goods is fundamental to truthful revelation of preferences. Skeptics suggest that without an actual monetary transaction people may lack the incentive to carefully examine their preferences and may be influenced by information provided in a hypothetical exercise that theoretically should not affect their underlying values. Psychologists have raised additional concerns, one of which is that the SV context may not provide a sufficient basis for individuals to formulate consistent and stable preferences for certain goods. They theorize that preference formulation is a

9. WTP and WTA are not necessarily equal, yet under conventional assumptions economists expect that the difference between them will be small. For private goods, this result generally holds as long as the amounts in question are a relatively small proportion of the individual's income. For environmental goods, Hanemann (1991) shows that this result does not strictly hold for changes in quantity or quality. Furthermore, if an environmental good has no close substitutes, the difference between WTP and WTA may be large even if income effects are small.

process requiring experience and familiarity with attributes of the good and the conditions for exchange.

In particular, critics have suggested that SV value estimates will not be comparable to revealed preference value estimates. In response to this critique, Carson et al. (1996) review comparisons between stated value results and revealed preference results (primarily travel cost and hedonic prices) for valuation of comparable quasi-public goods. Valuation studies for private goods were not included in their review. The goods included in the Carson et al. review include various forms of recreation (mostly outdoor recreation), changes in health risks, and changes in environmental amenities such as air pollution, noise pollution, water pollution, or parks. The review covers 83 studies containing 616 comparisons of SV and revealed preferences results. The authors conclude that, on average, the SV results are comparable to, or slightly lower than, the revealed preference results for similar amenities. A number of books have also reviewed issues in the implementation of SV studies as progress has been made in developing stated value methods (see Cummings et al., 1986; Mitchell and Carson, 1989; Bjornstad and Kahn, 1996; Kopp et al., 1997).

The goal of SV is to elicit individuals’ willingness to trade nonmarket goods and services for other goods and services, usually measured in monetary terms, under conditions consistent with those that make market transactions reliable measures of welfare change. Practitioners of SV have attempted to develop methods to make individuals’ choices in SV studies as consistent as possible with market transactions. Reasonable consistency with the framework of market transactions is a guiding criterion for ensuring the validity of stated preference (SP) value estimates. For instance, Fischhoff and Furby (1988) suggest three components of transactions to be constructed in SP surveys in order to emulate market transactions: the commodity (or good), the payment, and the marketplace.

Relative to information a respondent may already have about a commodity, SV studies need to define the commodity to be valued, including characteristics such as the timing of provision, certainty of provision, and availability of substitutes and complements. For weather forecast information, it is likely that individuals already have considerable experience with and a reasonable understanding of weather forecasts. This reduces the cognitive burden of defining and explaining the commodity compared to other commodities (such as the effects of airborne acid deposition on cultural monuments).

Respondents must also be informed about the framework of the transaction, including the method and timing of payment, and they should be aware of their budget constraints. The social context (the marketplace) is also defined to create incentives to enhance preference revelation, so individuals are able to identify their own best interests, and to minimize strategic behavior. When these conditions are met, it is more likely that individuals’ stated preferences will be consistent with economic measures of welfare change.

Selected SV Issues Addressed in the Survey

Scenario rejection, large WTP responses, and embedding issues are discussed here primarily with reference to the SV portion of the study. The stated choice portion of the survey also addresses scenario rejection, and there may also be embedding issues in the stated choice questions, which are discussed later.

Scenario rejection. Potential scenario rejection has been a longstanding issue in the SV literature. If the individual does not understand or believe some aspect of the hypothetical scenario, she may not state a true value for the commodity. In general it is suspected that individuals will state a zero willingness to pay if they reject the scenario. It is also possible that individuals will understate their true value if they feel uncertain about the commodity or the likelihood of its provision. Some researchers suggest that a high number of zero bids in an open-ended or payment card SV survey is evidence of potential scenario rejection. Because scenario rejection most likely cannot be eliminated from survey instruments, the most productive approach to dealing with scenario rejection is to identify potential scenario rejectors through debriefing questions or by examining responses to questions that would indicate that the individual does in fact have a positive value for the commodity.

In an effort to identify and account for potential scenario rejection, we include a debriefing question exploring individuals' motivations for their value statement. A factor analysis of these statements is used to generate a "rejection score" that is then included in regression analysis as an explanatory variable. Individuals with a high rejection score are expected to understate their true value or to state a zero value for the commodity. Not accounting for this potential bias could lead to significant underestimates of true WTP.

Large WTP responses. Several SV surveys have obtained WTP distributions with a thick tail of high WTP responses. While there are no a priori reasons to expect WTP distributions to *not* have a thick tail, since individuals are not actually required to undertake the transaction, it is possible some individuals may not state their true value for the commodity. Because WTP statements are usually truncated at zero, biased statements of value are more likely to be in the right tail of the WTP distribution. Calculated mean WTP may be sensitive to a small number of high stated WTP values. For this reason several researchers suggest reporting the median value as a better measure of central tendency in SV studies. Different methods have been suggested to control for large WTP responses in data analysis. One approach is to use a transformation of the WTP response such as a log transformation, which will put less weight on high WTP values. Another transformation used in analysis of SV responses is the Box-Cox transformation (see McClelland et al., 1993).

While we do not have a large number of high WTP responses, we have truncated the WTP distribution at $100 to partially control for possible large responses. Only about 8% of our WTP responses are $30 or higher.

Embedding. Embedding occurs if individuals are valuing a more comprehensive commodity than that intended by the researcher. In this study we are eliciting values for improvements in weather forecasts for day-to-day weather conditions. In focus groups and one-on-one interviews, it was apparent that some individuals were also considering the benefits of improved weather forecasts for severe weather events (e.g., tornadoes). Since it is not always feasible to change the way individuals perceive the commodity, an alternative is to recognize potential embedding and directly elicit information from individuals to control for embedding.

In this survey we include a debriefing question that asks individuals to state what percentage of the stated willingness to pay was for just day-to-day forecasts. This approach allows individuals to state the value they have for the commodity and then to refine their value statement. We explore the use of the WTP adjusted for self-reported embedding rather than the "raw" WTP in the analysis of WTP responses.

2.3.2 Stated Choice Analysis

Other stated preference methods include conjoint analysis, contingent ranking, and contingent behavior. These methods also use a hypothetical context in a survey format, but questions are designed as choices between, or rankings of preferences for, alternatives that include differences in goods and services as well as in costs. The alternatives that a subject prefers reveal information about his or her underlying values for the goods and services included in those alternatives.

Choice questions evolved from conjoint analysis, a method used extensively in marketing and transportation research.[10] Conjoint analysis requires respondents to rank or rate multiple alternatives where each alternative is characterized by multiple characteristics (see, e.g., Johnson et al., 1995; Roe et al., 1996). Choice questions ask respondents to choose the most preferred alternative (a partial ranking) from multiple alternative goods (i.e., a choice set), where the alternatives within a choice set are differentiated by their characteristics.

There are many desirable aspects of stated choice (SC) methods, not least of which is the nature of the choice being made. Choosing the most preferred alternative from some set of alternatives is a very common decision experience, especially when one of the attributes of the alternatives is a price. Johnson et al. (1995) note that "the process of evaluating a series of pairwise comparisons of attribute profiles encourages respondents to explore their preferences for various attribute combinations."

10. Cattin and Wittink (1982) and Wittink and Cattin (1989) survey the commercial use of conjoint analysis, which is widespread. For survey articles and reviews of conjoint, see Louviere (1988, 1992), Green and Srinivasan (1990), Batsell and Louviere (1991), and Adamowicz et al. (1998). Transportation planners use choice questions to determine how commuters would respond to a new mode of transportation or a change in an existing mode; Hensher (1994) provides an overview of choice questions as they have been applied in transportation. See also Ben-Akiva and Lerman (1994) and Louviere et al. (2001).

In stated choice the task of the respondent is to choose the most preferred alternative from each choice set. In this respect, this type of choice task is markedly different from the SV approach. Rather than being presented with one hypothetical state of the world and stating or choosing one's WTP for it, the stated choice task requires respondents to choose the good that is most preferred from multiple choice sets. One can argue that such a decision task encourages respondents to concentrate on the trade-offs between attributes rather than to take a position for or against an initiative or policy. This type of repeated decision process may also diffuse the strong emotions often associated with environmental goods, thereby reducing the likelihood of "yea-saying." Adamowicz et al. (1996) discuss this possible effect and also suggest that respondents are less able to behave strategically when responding to stated choice questions.

As with SV, choice questions allow for the construction of goods characterized by characteristics levels that (currently) do not exist. This feature is particularly useful in marketing studies when the purpose is to estimate preferences for proposed goods. For example, Beggs et al. (1981) assess the potential demand for electric cars. Similarly, researchers estimating the value of nonmarket goods are often valuing a good or condition that does not currently exist, e.g., weather forecasts that are accurate out to 14 days. When using stated choice questions to value nonmarket goods, a price, often a tax or a measure of travel costs, is included as one of the attributes of each alternative so that preferences for the other attributes can be measured in terms of dollars, i.e., WTP or WTA.

As in all elicitation techniques, the responses to choice questions may contain biases or random errors. Choosing can be difficult if the individual is almost indifferent between two alternatives. If each respondent is asked to answer a number of choice questions, there can be both learning and fatigue. Respondents can become frustrated if they dislike all of the available alternatives, and they may have no incentive for sufficient introspection to determine their preferred alternative. A number of studies have investigated these issues.[11] The general consensus is that if stated preference choice questions are carefully designed and implemented they can elicit important and relevant information about preferences, information that often cannot be deduced solely on the basis of observed behavior.

Choice questions, rankings, and ratings are increasingly used to estimate the value of nonmarket goods. For example, Magat et al. (1988) and Viscusi et al. (1991) estimate the value of reducing health risks; Adamowicz et al. (1994, 1997) and Morey et al. (1999) estimate recreational site choice models for fishing, mountain biking, and moose hunting, respectively; Adamowicz et al. (1996) estimate the value of enhancing the population of a threatened species; Layton and Brown (1998) estimate the value of mitigating forest loss resulting from global climate change; Breffle et al. (1999) assess values of recreational fishing service flow losses as a result of

11. For more details, see for example, Louviere (1988), Green and Srinivasan (1990), Agarwal and Green (1991), Gan and Luzar (1993), Bradley and Daly (1994), Mazzotta and Opaluch (1995), and Swait and Adamowicz (1996).

polychlorinated biphenyl contamination in the waters of Green Bay, Wisconsin; Bishop et al. (2000) conduct a choice-based total value equivalency study to assist restoration planning for the Green Bay area; and Morey et al. (in press) estimate WTP for monument preservation in Washington, DC. In each of these studies, a price (e.g., tax, or a measure of travel costs) is included as one of the characteristics of each alternative so that preferences for the other characteristics can be measured in terms of dollars.

Louviere (1994) provides an overview of choice questions as they have been applied in marketing. Adamowicz et al. (1997) provide an overview of choice and ranking experiments as they are applied to environmental valuation. It is argued that choice questions better predict actual choices than do rating questions because choice questions mimic the real choices individuals are continuously required to make, whereas individuals rank and rate much less often.[12]

Choice and rating questions characterize the alternatives in terms of a small number of characteristics. For example, Opaluch et al. (1993) characterize noxious facilities in terms of seven characteristics; Adamowicz et al. (1997) use six characteristics to describe recreational hunting sites; Johnson and Desvousges (1997) use nine characteristics to describe electricity generation scenarios; Mathews et al. (1997) use seven characteristics to describe fishing sites; Morey et al. (1999) use six characteristics to describe mountain bike sites; and Morey et al. (in press) use two characteristics to characterize monument preservation programs.

A variety of formats have been used in the design of choice questions. Choice questions may include choices between two or more alternatives, one of which may represent a status quo or baseline condition. This allows individuals to indicate that they prefer no change from the baseline. It may also involve a significant loss of data about how individuals value or trade off attributes if many respondents choose the no change alternative. In this study we first ask individuals to choose between alternative improvements in weather forecasts and then, in a followup question, allow them to indicate whether they would actually prefer to have no improvements made at no cost.

Analysis of this two-step choice process requires a conditional probit model in order to use all of the data generated in the choice process.[13] The conditional model accounts for the choice between doing nothing and pursuing the preferred forecast improvement alternative, given that a choice has already been made between two forecast improvement alternatives. Appendix F provides a derivation of the model used for evaluating the choice question responses.

12. See, for example, Louviere and Woodward (1983), Louviere (1988), and Elrod et al. (1992).

13. A conditional logit model could also be used depending on assumptions about the error term in the individual's utility function.

Fatigue and Learning in Stated Preference Responses. The ability of respondents to state preferences may vary across different types of questions or depending on how much time and effort respondents have spent on the survey. Estimating separate scale factors for different choice questions in the estimation of environmental preferences has been done to test for learning and fatigue effects (see, for example, Breffle et al., 1999, and Adamowicz et al., 1998). With learning, randomness may decrease; and with fatigue, randomness may increase. Swait and Adamowicz (2000) allow for the level of unexplained noise in choices to vary over choices and individuals using stated preference choices, and combining stated preference and revealed preference data. Scale parameters were allowed to vary with complexity, where complexity was represented by an endogenously determined overall measure of uncertainty called entropy (which increases in the number of alternatives and correlations between attributes). Mazzotta and Opaluch (1995) and Breffle and Rowe (forthcoming) present results supporting the hypothesis that increasing complexity in the choice task increases the associated noise in the choice.

As a direct approach to evaluate respondent comprehension, we ask respondents to state their level of comprehension of the stated preference questions. In this survey we ask respondents how confident they were in their answers to the choice questions and whether their responses to the choice questions should be considered by decision makers. These questions give an indication of the quality that respondents assign to their responses.

2.4 PERCEPTIONS OF WEATHER FORECASTS

The middle step in Hooke and Pielke's (2000) predict-communicate-use model deals with the communication and perception of weather information. Referring to flood forecasts, but equally applicable to all forecasts, Hooke and Pielke (p. 103) state that:

> while scholars have long recognized that communication involves both the *sending* and *receiving* information, little attention has been paid to the manner in which flood forecasts are interpreted by decision makers, and subsequently, to the role of this information in the forecast process [italics in original].

To our knowledge, the importance of communication in the valuation process has not been thoroughly examined. To create value to the public from weather forecasts, the step between prediction and use cannot be overlooked:

> . . . the challenge of providing more effective use of forecasts cannot be solved simply by providing "more information," such as improving the accuracy of existing products or developing new products, e.g., probabilistic forecasts. If decision makers have difficulty using existing products, the difficulties will not go away simply through providing more or "better" information (Hooke and Pielke, 2000, p.103).

Understanding households' perception of weather information involves the *receiving* part of communication. A limited number of studies have examined how individuals perceive and use weather information. We are not aware of any consistent or determined effort to examine the communication of weather information to households. Studies have generally addressed specific aspects of weather forecasts.

Murphy et al. (1980) report on an examination of laypeople's understanding of probability of precipitation forecasts in which 79 student subjects' preferences for numerical versus verbal information in precipitation forecasts were elicited in an 11-question survey. The questions distinguish between the subjects' understanding of the forecast event (likelihood of precipitation stated in a given forecast) and their understanding of probabilities (e.g., 70%). Results indicate that individuals misunderstand the event more so than the probabilities and that they have a preference for information stated in terms of percentages.

MSI Services Incorporated (1981) reports on a national telephone survey of 1,300 households' use of and need for weather forecast information. The survey was designed to answer eight general questions of interest to the NWS:

1. What types of weather information does the public use?
2. Does the public understand the information they are currently receiving?
3. What types of weather information does the public want?
4. How does the public obtain their weather information now and what method is preferred?
5. How often does the public want weather information?
6. How does the public feel about the value of the weather information they receive?
7. For what purpose does the public use weather information?
8. Is there a relationship between how close a person lives to a National Weather Service Office and how he/she perceives the service he/she is receiving?

The report presents summary statistics and cross-tabulations as well as some regional breakdowns. The current study covers all of these issues except for #8. Instead we explore how an individual perceives and values weather forecast information relative to a statistical measure of the accuracy of forecasts for his or her city. Several questions in the MSI work are similar to ones we are asking in the current survey and can be directly compared. These are discussed more in Chapter 4. The MSI study also included an SV question on the value of current weather information services. This is discussed in Section 2.5.2.

Murphy and Brown (1983) discuss the use of terminology in verbal public weather forecasts and what can be done to improve the transfer of information. Focusing on short-term weather forecasts, they define and consider (1) events, (2) terminology, (3) words versus numbers, (4) uncertainty, (5) amount of information, and (6) content and format of public forecasts and how these affect information transfer. Murphy and Brown suggest that individuals have a limited capacity to absorb and retain information and thus it is unnecessary for forecasts to provide excessive information. ". . . In determining the amount of information to include in a weather forecast, it appears that considerations related to . . . the recipient's ability to absorb, process, and recall information dominate considerations related to . . . the amount of information desired by the recipient” (p. 17). They further conclude that studies have found that, in general, temperature and precipitation are the most important part of the forecast message. Research recommendations include more study of public perception, use of, and understanding of public weather forecasts.

Curtis and Murphy (1985) discuss responses to a survey implemented through a newspaper in Seattle examining individuals’ interpretation of various terms used in weather forecasts. The survey was a self-administered newspaper questionnaire with over 2,000 responses. The results were compared with those from two questionnaires administered to college students in Oregon. Similar to prior findings, precipitation and temperature information was more important than cloud cover or wind. Numerical probability statements were preferred to verbal probability statements. Overall the results reported did not seem to indicate any significant misinterpretation of weather terminology by the public. There is no discussion in Curtis and Murphy of whether the interpretation of different weather terminology has any direct importance or how it may affect behavior.

Pope (1992) conducted a 48 question survey in 10 U.S. cities and towns exploring individuals’ use, understanding, and perceptions of weather forecasts. The general topics examined were weather information sources, quality and attributes of importance in the local forecaster, and understanding of severe weather. Location-specific differences were found that generally seemed to correlate with the locations’ weather. Respondents used TV as the primary weather forecast source (70.5%). Pope found that current, today’s, and the next day’s forecasts were the most important meteorological data displayed by local weather forecasters, over other data such as local radar, national weather, extended forecasts, satellite images, and jetstream maps. Individuals were generally indifferent between temperature being presented as a range versus a point description, but were generally in favor of percentage terminology rather than a descriptive term to indicate probability of precipitation. Similar to Murphy et al. (1980), Pope found general misinterpretation of “the event.” In this case a “50% chance of rain” was interpreted as meaning any one place in the forecasting area will have a 50% chance of rain (as opposed to the “correct” interpretation of only one specific place in the forecasting area will have a 50% chance of rain).[14]

Colman (1997) discusses briefly what makes a good weather forecast for the general public. A small convenience sample of weather forecasters was asked the question, and a majority answered that a good forecast was determined by the public’s response and perception of the forecast rather than by skill measures of accuracy: “. . . forecasters are concerned about public perception and the action the forecast instills” (p. 2). Colman provides two examples of similar forecasts of high wind warnings for the Seattle area, one that did not receive much public

14. While this seems to be a subtle distinction, technically it is considered a misinterpretation of the “event.” What is more important from the valuation perspective, though, is not whether the technical interpretation is correct but whether the behavioral responses are “appropriate” in terms of using the information inherent in the forecast. If individuals have a reasonable understanding of what the event implies, then a technical misinterpretation may be irrelevant.

reaction and one that did, but the author does not provide reasons why this difference occurred. Similar to the issues raised by Hooke and Pielke, Colman discusses that modernization has developed the technology for highly detailed weather forecasts but that the "technology" to best communicate forecasts to the public has not been developed. Several of the issues raised about communication and public perception are closely related to the risk perception literature (e.g., trust and credibility issues), but this literature is not specifically referred to.

While the literature on individuals' perception and understanding of weather information is limited, several studies suggest that there is some misunderstanding of the weather information presented to the public. While not specifically the focus of the current study, we agree with Hooke and Pielke's contention that "more attention must be paid to *how* forecasts are issued, *who* actually receives *what* information, and with what *effect*" (p. 103, italics in original).

2.5 STUDIES OF THE VALUE OF WEATHER FORECASTS

2.5.1 Prescriptive and Descriptive Valuation Approaches

In categorizing valuation approaches, Murphy (1994) distinguishes between (1) prescriptive approaches (behavior in accordance with normative principles such as utility maximization or loss minimization) and (2) descriptive studies (focusing on actual behavior as in decision making or information processing) (see also Freebairn and Zillman, no date–b). Most prescriptive studies posit a loss function or its inverse, a payoff function (e.g., Davis and Nnaji, 1982; Ehrendorfer and Murphy, 1992). Because these loss functions are generally a statement of how households *should* value weather information, they generally are not useful in eliciting or understanding how households actually *do* value weather information. Furthermore, in positing a loss function, prescriptive approaches generally do not incorporate any manner of risk aversion on behalf of the decision maker.

There are hundreds of studies of the value of weather, but fewer of the value of weather information. Using Murphy's terminology, most studies are prescriptive in terms of examining idealized behavior given a change in the information available to the decision maker. Johnson and Holt (1997) and Wilks (1997) review dozens of such studies, mainly in the agriculture sector. Murphy (1994) includes an annotated bibliography of studies of the value of forecasts indicating (1) approach/method, (2) type/range of forecasts, and (3) sector of application.

Stewart (1997) updates an earlier literature review of descriptive studies of the value of weather information and classifies them into four general types of studies: (1) anecdotal reports and case studies, (2) user surveys, (3) interviews and protocol analysis, and (4) decision experiments.

Stewart (p. 155) notes that while " . . . in principle, a descriptive model could be used to estimate the monetary value of forecasts, this process has rarely been completed." He does not appear to cite any such studies or values derived from them. In general Stewart (p. 159) is skeptical of the use of survey approaches for eliciting such values: "Some surveys have asked users to estimate the value of forecasts in monetary terms. It is highly unlikely that a user can provide a valid estimate of the economic value of a forecast (see the literature on stated value studies for a list of reasons why, e.g., Fischhoff and Furby, 1988; Mitchell and Carson, 1989).” Stewart fails to note that Mitchell and Carson actually conclude that that SV can provide valid estimates of nonmarket goods and services, especially those comprising largely use values.

Stewart states that “Murphy and Brown point out that surveys are inherently flawed, because they are based on users’ *perceptions* of needs rather then on a descriptive or prescriptive decision model” (p. 159, italics in original). Stewart continues on to state that “surveys can, however, be used to examine the determinants of subjective forecast value” (p. 159). Stewart and others such as Murphy and Brown (1983) seem to dismiss the values that individuals have for weather forecasts as elicited in surveys if their behavior does not conform to the prescriptive models. It must be noted though that, from the perspective of welfare economics that serves as the basis of benefit-cost analysis, individuals’ subjective values *are* the valid measures of welfare change.

The approach taken in the present study, as in most nonmarket benefit elicitation approaches, is to assume that individuals behave consistent with utility maximization. In other words, we assume that their behavior is consistent with maximization of the utility function we assume for them. To this extent, such approaches are “prescriptive.” Such approaches are also descriptive to the extent that they focus on actual behavior (or contingent behavior in the case of stated preference approaches).

2.5.2 Valuation Studies

Prototype Regional Observing and Forecasting Service (1979) reports on research conducted by J.E. Haas and R.B. Rinkle of Human Ecology Research Services in Boulder, Colorado. Values for improved local weather forecasts were elicited from 95 Denver urban area households. Residents were interviewed to examine their use of forecasts for various work and recreation activities. After discussing forecasts for different weather conditions with different lead times, individuals were asked to estimate benefits from improved or perfect weather forecasts. Values were elicited in terms of their savings in undertaking different activities such as recreation, commuting, or shopping. The majority of subjects were unable or unwilling to make a value statement. Treating nonresponses as zero value, values were estimated on a per forecast basis for type of forecast (e.g., hail, snow, rain). Estimated aggregate benefits for perfect forecasts for Denver households were $31 million (1979$) based on estimated annual per capita benefits of $44 for commuting, $17 for recreation, and $23 for shopping weighted by the number of activities undertaken.

MSI Services Incorporated (1981) reports on a national telephone survey of 1,300 households’ use of and needs for weather forecast information. The survey included a valuation question on what individuals think the value of their weather information is: “If you had to put a dollar value per year on weather information you receive, what would it be?” Depending on how the upper bound of the highest category is treated, the mean WTP is between $20.72 a year and $27.20 a year. Given reasonable practices in stated value studies, the value estimate derived from this report is of questionable use: the question was the 51st question in a 59 question telephone survey; the commodity being valued, “weather information you receive,” is extremely vague even given the preceding questions; and the valuation scenario did not identify a payment mechanism, discuss complements or substitutes, or check for validity or reliability of responses.

Anaman et al. (1995, 1997, 1998) and Anaman and Lellyett (1996) describe a seven project, multiyear study of various aspects of the value of weather information services provided by the Bureau of Meteorology (BoM) of Australia. Two of the seven projects used stated value methods to elicit values for weather information; Project 1 elicited Sydney area residents’ values for BoM services and Project 7 elicited household values for the Tropical Cyclone Warning System (TCWS) in Queensland. Anaman and Lellyett (1996) report on a short telephone SV survey administered to 524 adults in Sydney eliciting values for the Australian public weather service. Average monthly WTP was AU$2.00, with 62.5% reporting zero WTP. A logistic regression indicated lower WTP from older people, higher WTP from more frequent users and from those judging the information to be of higher quality, and no significant relationship for the additional use of weather information in business as well as personal use. The logistic regression modeled WTP as 0 for zero WTP and 1 for positive WTP.

Chapman (1992) prepared a benefit-cost analysis of the (then) proposed NWS modernization, including a sensitivity analysis. In general Chapman found strong support for the modernization using any criteria (benefit-cost ratio or net present value). The benefit estimate relies heavily on a value derived from the 1981 MSI Services report “Public Requirements for Weather Information and Attitudes Concerning Weather Service.” The per capita value from the MSI Services study was translated to $35.50 per year ($1992). Even given adjustments made to the MSI Services study values for use in the benefit-cost analysis of the weather service modernization, there is nothing in the MSI Services study that would indicate a specific relationship between values for current services (as elicited in the MSI Services study) and values for changes in services (as required for benefit-cost analysis of the modernization).

Cavlovic et al. (undated — b) surveyed 624 individuals to elicit values for Weatheradio in Canada. Weatheradio, run by Environment Canada, provides weather warnings along the Atlantic coast of Canada and thus is primarily a weather warning system. A telephone-administered, double-bounded dichotomous choice contingent valuation survey was used. The survey also elicited information on other sources and uses of weather information and preferences for improvements to Weatheradio. Average annual WTP for Weatheradio was derived for residents of New Brunswick ($96.27CA per user, business or personal), Nova Scotia ($76.47CA), and Prince Edward Island ($93.12CA) for an aggregate value of slightly over $2 million (CA) annually.

In a related study, Cavlovic et al. (undated — a) value Environment Canada’s Weatherline Automated Telephone Answering Device (ATAD) weather information service, focusing specifically on business callers from the Toronto area. Cavlovic et al. estimate a mean WTP per call of $1.20CA, which varies depending on the type of business using the information.

CHAPTER 3
SURVEY DEVELOPMENT, DESIGN, AND IMPLEMENTATION

3.1 SURVEY DEVELOPMENT

3.1.1 ASA Service Packages

Background information on potential weather forecasting improvements was provided by Atmospheric Science Advisors, LLC (ASA). The ASA document "A Discussion of Selected Weather, Water and Climate Forecasts and Services: Pilot Study of the Value of Improved Weather Forecasts" (July 25, 2000) provides background information on the scope of weather service operations. Five service packages for different types of weather information are covered in the draft, of which the first, "Improve the Daily Weather Forecast," is the primary focus of the current research. ASA provided information on weather forecast elements; the accuracy, specificity, length of forecasts; and the frequency of updates. ASA also provided information on potential improvements in daily weather forecasts, the range of improvements possible, and estimated costs of improvements. The other service packages to be examined in future research include:

- improve severe weather forecasts and warnings
- improve river stage forecasts
- improve forecasts for large scale weather systems
- improve seasonal to interannual forecasts.

Throughout the survey development process, ASA advised Stratus Consulting on weather information incorporated in the survey, and observed several of the focus groups and one-on-one interviews.

3.1.2 Focus Groups and One-on-One Interviews

The initial focus group with 15 subjects focused largely on how to define attributes of weather forecasts. The preliminary work explored terminology laypeople use to discuss weather information, where they get weather information from and how they use it, and approaches to eliciting values for changes in weather information. A modified open-ended approach was used to allow us to elicit information without constraining respondents. Open-ended questions were used to examine individuals' understanding of weather information and the words and meanings they use normally to "talk about the weather." Directed questions were used to examine the relative importance of weather forecast attributes to the subjects and to begin defining levels to use in presenting scenarios to individuals for valuation. Through this work we assessed approaches for developing a survey instrument to be used to elicit households' values for improved weather forecast information.

Based on the focus group results, an initial survey instrument was drafted. Through three rounds of one-on-one interviews using methods from verbal protocol analysis (Ericsson and Simon, 1993), the instrument was refined and a pilot instrument was developed. Eleven one-on-one interviews were conducted, each lasting up to one and a half hours. In verbal protocols, individuals read through and complete the survey while speaking out loud the entire time they are working on the survey, a process of verbal reporting called "think alouds." A moderator listens the entire time without interrupting or asking or responding to questions. This allows the moderator to see if the respondent has any particular problems with the wording, formatting, or other aspects of survey design. If particular issues arise during the process, the moderator can use retrospective probes to further explore these issues.

Between each round of one-on-one interviews, the instrument was reviewed and edited extensively by Stratus Consulting staff and comments elicited from ASA personnel. Throughout survey development, emphasis was placed on defining the attributes of weather forecasts in a way that was meaningful to and understandable by lay respondents.

3.1.3 Denver Survey Pilot Test

A pilot study of 84 subjects in the Denver Metropolitan area was conducted in March 2000. The pretest site, and pilot test size and nonrandomness of the sample limited the generalizability of quantitative results. The pilot test was sufficient, though, to assess the survey instrument and valuation approach. The pilot survey used the three different stated preference nonmarket valuation approaches to elicit household values for current or improved weather forecasting services. Analysis of the stated choice questions in the pilot survey indicated that improving the accuracy of one-day forecasts was valued most, followed by improving the accuracy of multiday forecasts and geographic detail. Overall, individuals appeared to have little value for increasing the frequency of weather forecast updates. Using the values estimated for changes in the attribute levels, we calculated individuals' value for a program that would increase all attributes to their maximum level between $9 and $18 a year per household.

Our analysis of the valuation responses indicated that values for improving weather forecasts were related to sociodemographic characteristics such as income and education, how much time an individual spends outdoors on the job, and how individuals use weather information in making behavioral decisions (such as what to do on the weekend). It was also found that individuals' WTP statements were influenced by how they viewed the scenario presented to them for valuation. The average WTP for the "maximum" improvement in weather forecasting program ranges from $8 to $15 a year per household (for our sample of Denver households), depending on how we treat individuals answers to the followup questions. These values were very close to those derived from the stated choice valuation questions.

The third valuation question asked individuals if the services they currently receive from the NWS are worth what they currently pay in taxes for these services. By varying the amount indicated as the current cost to taxpayers, we examined how willingness to pay for current services varies. With current costs to taxpayers of about $13.20 a year per household for NWS services (see Section 5.4), there would appear to be significant excess benefits generated by current weather service activities. More than 86% of individuals indicate they are willing to pay at least $10 for current NWS services.

The pilot survey also elicited information on what characteristics are most useful to individuals in weather forecasts and current observations. As in prior studies, we found that precipitation and temperature were the most important components of weather forecasts and of current weather observations. Some weather information characteristics (such as dewpoint or barometric pressure) were infrequently used and may have been poorly understood by the general public.

Statistical analysis of subjects' responses indicates that there were differences between individuals in how important certain characteristics of weather forecast information were. For instance, wind strength was more important to those who work outside more, and high temperature and extent of cloud cover were more important to those whose spend more leisure time outside. Differences also existed between individuals in their use of weather forecast information for planning social or recreational activities. The use of forecasts for work around the house or yard, and for job, business, or farm activities, was more important to whose spend more leisure time outside. Differences between individuals in their use of weather forecasts lead to differences in values for improvements in weather forecasts.

3.1.4 Final Revisions and Review

In January 2001 we conducted an external review of the survey instrument with three survey design and implementation experts. Three experts participated in the review process: Johnny Blair of the Survey Research Center at the University of Maryland; Nora Cate Schaeffer, professor of sociology at the University of Wisconsin; and Roger Tourangeau of the University of Michigan and University of Maryland and director of the Joint Program in Survey Methodology at the University of Maryland. Each reviewer received copies of the survey instrument and the interim report on the Denver pilot study. Following their individual review a telephone conference was held to discuss and clarify specific concerns and suggestions for survey design and improvement.

Following revisions based on the Denver pilot test and the expert review panel, we conducted additional one-on-one interviews and focus groups in Raleigh, North Carolina, in February 2001. The purpose of these interviews was to examine whether there may be significant locational or regional differences that we needed to be aware of and incorporate into the survey instrument. In general we found no significant differences between the North Carolina subjects and those in Colorado. Although they had different experiences with weather phenomena, the survey instrument was adequate for implementation with these different groups.

Some of the differences between the Denver pilot and final survey are that the final survey:

- included an additional (higher) $24 level for the stated choice questions
- had 20 versions rather than the 6 used in Denver (the only thing differing between versions is the levels of attributes in the stated choice questions, the attribute levels in the WTP question, and the current costs of weather forecasts indicated in the followup questions)
- included a section designed to remind individuals of their budget constraint
- indicated a base level of four weather forecast updates daily (rather than three a day used for the Denver pretest survey)
- dropped several questions because of limited space to focus on the specific research issues, including questions on the characteristics of current forecasts, bequest and altruistic motives for willingness to pay
- redesigned the value of current forecast question expanding the range of dollar values and providing respondents more information on current forecast services
- shortened the followup section on severe weather.

3.2 VALUATION QUESTION DESIGN

The survey incorporates three different types of valuation questions, each with different functions. First, the SC questions are designed to examine individuals' tradeoffs between the attributes of improved weather forecasts. From this information we can derive individuals' marginal values for these attributes. Second, the SV question elicits individuals' value for improving weather forecasts under various specific improvement scenarios. The SV question also allows us to explore issues of scenario rejection and embedding. We combine the analysis of the SC and SV questions to take advantage of the strengths of the different question formats. Third, a valuation question is incorporated in the followup portion of the survey to elicit limited information on individuals' value for all current weather forecasting services provided by the NWS. Values for current weather services are fundamentally different than those for improved forecasts as elicited in the other valuation questions.

3.2.1 Choice Question Choice Set Design

A primary focus of the survey design and pre-testing was choosing the appropriate attributes of the weather forecasts and determining current levels and feasible levels under potential improvements. Based on input from ASA on NWS services and potential forecasting improvements and based on prior studies of individuals' perceptions of and value for weather forecasts, we focused on four attributes: frequency of updates (times per day), accuracy of one-day forecasts, accuracy of multiday forecasts, and geographic detail.

Levels

Based on information provided largely by ASA and supplemental information from NWS personnel, we chose baseline levels of these attributes and potential levels with improved weather forecasts to develop the choice questions. These levels are shown in Table 3-1. The implicit cost of baseline services is zero additional cost to households.

Table 3-1
Attribute Levels for Weather Forecasts

Attribute Level	Frequency of Updates (times per day)	Accuracy of One-Day Forecasts	Accuracy of Multiday Forecasts	Geographic Detail[a]
Baseline	4	80%	5 days	30 miles
Minimal Improvement	6	85%	7 days	15 miles
Medium Improvement	9	90%	10 days	7 miles
Maximum Improvement	12	95%	14 days	3 miles

a. Area of the United States = 3,536,338 sq. mi. Divided by ~3000 counties => average county size is about 1,178 square miles or about 35 miles x 35 miles. As per Rosenfeld (2000b), this is currently about 20 miles in NWS models.

In the choice questions, individuals choose between alternatives represented by combinations of different levels of the four forecast attributes outlined in Table 3-1. Each alternative also includes its cost to the household, as an increment to annual taxes. Dollar values were chosen based on pretesting to cover the range of reasonable potential costs that would not induce significant rejection on the part of respondents. If too high of a value is included in a choice set, all individuals will reject the alternative and little useful information can be extracted from the choice set. If dollar values are too low, they may be ignored and will also lead to little useful information. Dollars per year per household of $3, $8, $15, $24 were used to indicate the cost of weather forecast improvement programs. Dollar values between $3 a year and $24 a year seemed reasonable to individuals during pretesting. The $24 level was added after the Denver pilot test, which indicated that individuals had values above $15 for some of the forecast improvement scenarios.

Choice Set Design

We developed 20 versions of the survey that differ only in the levels of the attributes offered in the choice sets and the stated value question (and in the dollar values suggested in the followup valuation question discussed later; see Appendix C for more information on choice set design). Since each version included 9 choice sets, there were 180 different choice sets. The first choice set question in each survey version, Question 15, was primarily an example of how the choice questions were to work. Only two weather forecasts attribute levels were varied in these example choice questions so that individuals would get used to the idea of trading off attributes; dollar values were constant. For Question 15 only, an extra column on the right-hand side of the page highlighted the differences between the two alternatives. This approach has been found to enhance respondents' ability to understand the choice question process.

The other eight choice questions, Questions 17, 19, 21, 23, 25, 27, 29, and 31 (see Figure 3-1), were designed using an approach for optimal experiment design discussed in Kuhfeld (1996). The basic approach is to choose attribute levels throughout all of the choice sets to maximize the ability to identify marginal values. Appendix C includes a technical discussion of the choice set design.

Questions 16, 18, 20, 22, 24, 26, 28, 30, and 32 (see Figure 3-2) asked respondents whether they preferred to go with the option they had just chosen or would rather that nothing be done at this time to improve weather forecasts and that no additional taxes be levied. The answer to this question is conditional on the answer to the A-B choice question. If the individual chooses "do nothing," then it can be assumed that she prefers that nothing be done over either A or B. This allows for a complete ranking between the three alternatives (A, B, do nothing). If the individual chooses to stay with the alternative chosen in the choice question, then a complete ranking is not possible because it is not known whether the individual prefers to "do nothing" or to do the unchosen alternative from the choice question.

3.2.2 Stated Value Question Design

Question 33 poses a stated value WTP question for a program to improve weather forecasting under specific programs that differ across the 20 versions of the survey (see Figure 3-3). Attribute levels were designed using a similar approach as that for the stated choice questions although the do nothing (current) alternative was implicitly constant for all versions of the survey.

Table 3-2 shows the correlation between attribute levels in the stated value question across the 20 different versions of the survey. Relatively uncorrelated attribute levels is necessary to separate value estimates for individual attributes.

Figure 3-1
Example Choice Question

17 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	9 times a day	12 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 90% of the time	correct 85% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 14 days in the future	accurate up to 14 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 7 by 7 miles	to 30 by 30 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$15 more	$8 more
Check (✔) the box for the program you prefer →	☐	☐

Figure 3-2
Choice Question Follow-Up

18 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?**
Circle the number indicating your preference.

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.
2. Make the improvements in the program I that chose above and pay the amount indicated.

A "payment card" value elicitation approach is used. This approach is less data intensive and provides a more direct statement of individuals' willingness to pay than referendum approaches. It may also be easier to answer than open-ended willingness-to-pay formats. The payment card was designed to minimize potential range and centering biases and to offer a sufficiently high upper-end value to avoid truncating value statements (Rowe et al., 1996). An approximately exponential value scale is used with 25 specific values and an "other" option.

Several followup questions are included to help understand individuals' responses to the SV question and to adjust for potential scenario rejection and embedding issues. Question 34 includes multiple scales that indicate how these issues influenced individuals' responses to the SV question. Factor analysis of this questions allows us to generate a "scenario rejection" score to include as an explanatory variable in the regression analysis (for another application of this approach, see Kinnell et al., 2002). Question 34 also includes a scale that provides information on individuals' attitudes about privatization of weather service functions. Questions 35 and 36 identify and scale potential embedding in the SV response.

As a direct approach to evaluate respondent comprehension, we ask them to state their level of comprehension of the stated preference questions. Question 38 asked how confident respondents were in their answers to the choice questions, and Question 39 asked whether their responses to the choice questions should be considered by decision makers. Recognizing that the choice questions may be difficult for some respondents, these questions are intended to give an indication of the quality that respondents assign to their responses.

Figure 3-3
SV Valuation Question

33 **Now consider the following specific weather forecasting improvement program involving a combination of new satellites, radar, computers, computer programs, and weather service personnel. This specific program would improve the weather forecast as indicated in the following table:**

	CURRENT	WITH IMPROVEMENT PROGRAM
FREQUENCY OF UPDATES	4 times a day	4 times a day
ACCURACY OF ONE-DAY FORECASTS	80% correct	95% correct
ACCURACY OF MULTIDAY FORECASTS	Accurate up to 5 days into the future	Accurate up to 14 days into the future
GEOGRAPHIC DETAIL	Detail within 30 by 30 miles	Detail within 7 by 7 miles

If this improved program were the only program that the NWS was considering, what is the most your household would be willing to pay each year, in addition to what you are now paying? Remember that this annual payment would continue as long the improvements in weather forecasts were maintained. *Circle the dollar amount indicating the **most** your household would be willing to pay each year.*

$0	$1	$2	$3	$4	$6
$8	$11	$14	$17	$21	$26
$31	$37	$43	$49	$56	$64
$73	$83	$94	$100		

Other $__________

Table 3-2
Correlation between Attribute Levels in Stated Value Question (n = 20)

	Frequency of Updates	Accuracy of One-day Forecasts	Accuracy of Multiday Forecasts	Geographic Detail
Frequency of Updates	1.000			
Accuracy of One-day Forecasts	0.070	1.000		
Accuracy of Multiday Forecasts	0.083	0.080	1.000	
Geographic Detail	-0.044	-0.110	-0.088	1.000

3.2.3 Value for Current Forecast Services Follow-Up

Question O2 in the followup questions examined individuals' value for the current level of weather forecasting services. Figure 3-4 shows one version using the $10 a year level. Other versions used between $2 a year and $96 a year, as indicated in Table 3-3. Actual current expenditures are about $13 per household for NWS services (see Section 5.4). If individuals value current weather forecasts at different levels, then, because the percentage willing to pay a given amount drops as the dollar cost increases, a demand curve can be drawn out over the range of prices offered. While not measuring WTP directly, it is implicit that if current services are at least worth current costs then WTP for current services equal or exceed current costs.

Table 3-3 shows the different dollar values as inserted in the 20 different versions of the survey. These dollar values were randomly assigned to survey versions independent of the attribute levels presented in the SC and SV questions.

3.3 FINAL SURVEY

The final survey instrument is presented in Appendix B. The 20 versions of the survey differed only in the levels of attributes presented in the choice questions (Questions 15 through 31), the attribute levels in the improvement program for the stated value question (Question 33), and the dollar amount indicated in Question O2, the followup question on individuals' value for current weather services. Appendix D provides attribute levels for each of the 20 different versions of the stated choice questions.

Figure 3-4
Value of Current Weather Forecast Services Valuation Question

O2 **All of the activities of the NWS are paid for through taxes as a part of the federal government. This money pays for all of the observation equipment (such as satellites and radar), analysis, and reporting activities of the NWS. As discussed above, in addition to normal weather observations and forecasts, the NWS provides services such as severe weather forecasts, including watches and warnings, forecasts used for aviation and marine commerce, and information provided to private weather services.**

Suppose that you were told that about $10 a year of your household's taxes went to paying for all of the weather forecasting services of the NWS and the federal government. Do you feel that the services you receive from the activities of the NWS are worth more than, less than, or exactly $10 a year to your household? *Circle the number of your answer.*

1. Currently worth less than $10 a year to my household
2. Currently worth $10 a year to my household
3. Currently worth more than $10 a year to my household

Table 3-3
Options for Question O2

Survey Version	$(fill) Value
5, 9, 13, 15	$2
4, 6, 14, 17	$5
1, 3, 8, 10	$10
7, 11, 12, 18	$32
16, 19	$64
2, 20	$96

The entire written survey is 33 pages long (plus a cover page and an end page). Technically the entire survey process includes the telephone screener, which obtained sociodemographic information on the respondents that is combined with the data from the written survey. Table 3-4 outlines the survey design for the written survey instrument, indicating the purpose of the various sections and questions throughout the instrument.

The first portion, up through Question H9, is the basis of a potentially mailable survey instrument. Questions O1-O6 are included to elicit additional information on individuals' value of current weather information and to begin exploring issues related to other service packages.

Table 3-4
Outline of Survey Instrument

Questions	Purpose
Q1-Q4	Perceptions, uses, and source of weather forecasts
Q5-Q12	Weather forecast attributes and attribute levels
Q13-Q14	Introduction of scenario for improved weather forecasting and budget constraints
Q15-Q32	Choice questions for weather forecast improvements
Q33	SV questions for weather forecast improvements
Q34-Q39	SV and choice question debriefing
H1-H9	Sociodemographics (additional sociodemographic information elicited in the telephone recruitment screener)
O1-O2	Value of current weather forecast services
O3-O6	Severe weather effects and information

3.4 IMPLEMENTATION

3.4.1 Choice of Implementation Sites

The study elicited values from individuals in nine different cities in market research settings. The cities were chosen one each from the nine regions defined by the National Climate Data Center for climate summaries (Figure 3-5). The cities are San Diego, California; Portland, Oregon; Denver, Colorado; Billings, Montana; Oklahoma City, Oklahoma; Madison, Wisconsin; Columbus, Ohio; Albany, New York; and Miami, Florida. Cities from different regions were chosen as much to capture interregional variation in sociodemographics as to capture values based on potential interregional differences in climate characteristics and weather forecasting quality.

Figure 3-5
NCDC Climate Regions

3.4.2 Climate Data for Selected Cities

Historical data on weather forecasts and observed weather conditions were used to create indices of weather variability and forecast accuracy. We focused on temperature data because the Denver pilot test and prior research indicated temperature was of primary importance to households in weather forecasts. We examined minimum and maximum temperatures and created indices based on both forecasts and actual temperatures. These are used to explore how individuals' perceptions of and values for improved forecasts and current forecast services relate to local weather variability (e.g., persistence) and the quality of forecasts available to the respondents (e.g., skill). Recognizing that weather forecasters have a multitude of approaches for measuring forecast accuracy (Murphy, 1997) we were attempting to derive relatively simple measures of forecast accuracy and weather variability, not as measures of NWS capabilities, but purely as an input to understanding individuals' perceptions, uses, and values for forecasts.

Forecasted temperature data are from the NWS Statistical Modeling Branch (SMB). This database consists of archived midrange forecasts (up to seven days out) for all major stations in the United States and was downloaded from http://isl715.nws.noaa.gov/mos/archives/mrffox/.

The day-ahead minimum and maximum temperature forecasts used in this analysis were from January 1994 through December 2000. For example, on January 2, 2000, the forecasted maximum temperature for Denver, Colorado, was 37°F. This prediction came from the NWS on January 1, 2000. Day-ahead forecasted temperature extremes are then compared to actual minimum and maximum temperature readings to provide us with a benchmark for accuracy in the forecast. Historical daily temperature data are from the National Climatic Data Center (NCDC). Recorded daily minimum and maximum temperature data used in this analysis cover from January 1994 through December 2000.

As a measure of forecast reliability we calculated the average of the absolute value of the difference between the forecast minimum (maximum) temperature and the observed minimum (maximum) temperature over the 7 year period from January 1994 through December 2000. Table 3-5 displays the mean and variance of the forecast error for each of the nine cities in this analysis. For instance, the value indicated as "Max temp forecast error" in Table 3-5 is calculated by:

$$\text{Max Temp Forecast Error} = \frac{\sum_{i=\text{January 1,1994}}^{i=\text{December 31,2000}} \left|\text{Forecast Max Temp}_i - \text{Actual Max Temp}_i\right|}{\text{number of days January 1,1994 and December 31,2000}}$$

(accounting for any missing data).

Table 3-5
Analysis of Absolute Value of Error in Minimum and Maximum Temperature Forecasts from January 1994 through December 2000

	Min Temp Forecast Error (°F)		Max Temp Forecast Error (°F)	
City	**Mean**	**Variance**	**Mean**	**Variance**
Albany, NY	3.95	12.57	3.78	9.36
Billings, MT	3.75	12.79	4.37	15.10
Columbus, OH	3.58	10.60	3.60	9.02
Denver, CO	3.43	9.60	5.33	23.73
Miami, FL	2.33	4.16	1.95	3.16
Madison, WI	4.39	14.81	3.92	10.26
Oklahoma City, OK	3.83	12.78	4.71	15.00
Portland, OR	2.57	4.21	3.40	7.46
San Diego, CA	1.80	2.25	2.68	5.45

As a measure of day-to-day weather variability (e.g., persistence), we calculated how much minimum (maximum) temperature changed from day to day. Specifically we calculated the mean of the absolute value of the 24 hour change in the observed minimum (maximum) temperature for each city for January 1994 through December 2000. Table 3-6 displays the mean and variance of temperature changes for each city.

Table 3-6
Analysis of Absolute Value of 24 Hour Temperature Changes for January 1994 through December 2000

	24 Hour Min Temp Change		24 Hour Max Temp Change	
City	**Mean**	**Variance**	**Mean**	**Variance**
Albany, NY	5.89	24.19	5.86	26.11
Billings, MT	5.08	22.95	7.48	40.68
Columbus, OH	5.37	21.54	5.98	29.15
Denver, CO	4.44	16.42	7.86	47.05
Miami, FL	2.75	8.28	2.44	7.75
Madison, WI	5.97	25.65	5.72	26.32
Oklahoma City, OK	4.91	18.71	6.08	31.49
Portland, OR	3.22	6.94	4.57	14.72
San Diego, CA	1.82	2.92	2.81	8.05

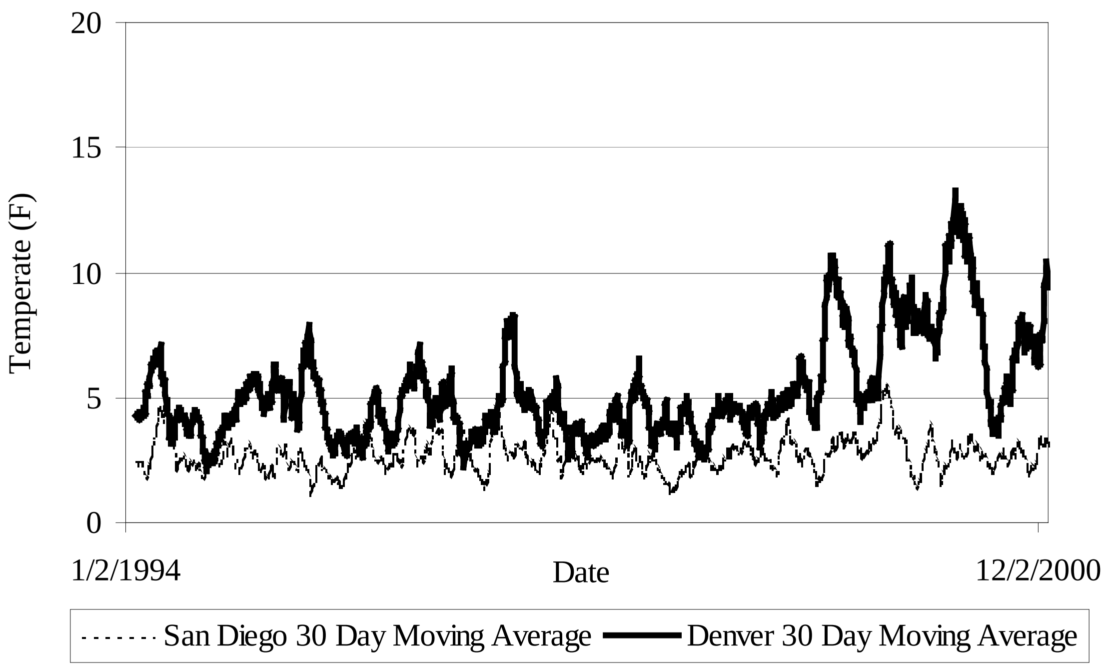
Figure 3-6 shows the difference in forecast error between Denver and San Diego using a 30-day moving average. Overall this would suggest that temperature forecasts are more accurate in San Diego than in Denver.

As seen in Tables 3-5 and 3-6, all of the measures are highly correlated across the nine cities. Since high temperatures are relatively important to individuals (see Table 4-7), the analysis that follows generally uses the one-day forecast error for the maximum temperature for analysis of individuals' perceptions of and values for weather forecast improvements.

3.4.3 Sampling

The method for this study consisted of a telephone recruitment survey followed by a central site survey. The telephone recruitment survey was used to screen for participants. The sample for this study consisted of a random digit dial (RDD) sample of households in the nine selected cities. Sample sizes were slightly larger for Denver, Albany, Madison, and Miami, where it was

Figure 3-6
Comparison of Differences (30 day moving average) in San Diego, California, and Denver, Colorado
(absolute value of forecasted maximum temp — actual maximum temp)



determined that extra recruiting was necessary. Columbus was also over-recruited, but with no increase in sample. Sample was limited to households within 7 or 10 miles of the chosen facility. This sample was obtained from Survey Sampling Inc., a well-known provider of survey samples. Before the sessions, the households agreeing to complete the survey were randomly assigned to receive one of the 20 different versions of the final survey instrument.[1]

1. Survey Sampling, a subcontractor to PA, provided a 10-digit randomly generated number. The samples were drawn from a radius around the central site based on a 7-mile radius [Portland, San Diego, Columbus, Oklahoma City, Billings, Clifton Park, New York (Albany), Madison] or a 10-mile radius (Miami, Denver). Numbers were eligible for the sample if any part of the zip code they were in fell within the 7 or 10 mile radius. For the residential sample Survey Sampling then screened out business, fax and nonworking numbers. Thus, everyone with a phone in these zip codes had an equal probability of being selected regardless of whether or not their phone is listed.

3.4.4 Survey Implementation

The following procedures were used:

- *Telephone recruitment screener*. Discovery Research Group conducted the telephone recruitment screener survey a week and a half before each scheduled session. Recruiting for Denver and Miami initially started before September 11, 2001. After September 11, both sessions were rescheduled, which resulted in rerecruiting for both Denver and Miami. Discovery Research used a minimum of three attempts to reach sampled phone numbers. The recruitment survey averaged 6-7 minutes. The telephone recruitment screener is included in Appendix A.

- *Confirmation*. Discovery Research Group sent confirmation letters each day after recruiting. Confirmation calls were made for 2 days before each session. Anyone refusing or canceling at that time was removed from the list and replaced with another recruit.

- *Recruit data file*. Discovery Research Group provided an electronic file of all recruits for each session to PA Consulting the morning of the session. This file contained the name and address of the recruit, as well as the data from the recruit survey. PA assigned a survey ID and prepared a check-in sheet for the session host.

- *Survey packet.* The survey was labeled with an ID and inserted in an envelope with the same ID. Envelopes were sealed and sent to each site. It was important it ensure that respondent telephone screeners were matched with the written surveys through the ID numbers.

- *Session procedure.* Participants were checked in and given a survey envelope with their corresponding ID. At the beginning of each session the participants were read the instructions as a group. Session instructions were audiotaped and videotaped where available. As participants finished they were checked out. Surveys were checked for completion, the survey ID was recorded again, and participants signed their name as proof of receiving the $40. The central site surveys averaged about 45 minutes. Thirty minutes was the quickest anyone finished and a few individuals took a full hour. Sessions in Denver, Miami, and Madison were observed by Stratus Consulting or PA Consulting staff.

- *Deliverables.* Implementation facilities shipped all surveys back to PA Consulting, where they were checked in and the data were entered and double checked for entry accuracy. All audio and videotapes were returned to Stratus Consulting for review in the event of data problems.

- *Additional mail surveys.* Because the initial show rate was so low in Miami, calls were made to any recruited subjects who did not attend the sessions. They were offered $10 to complete and return the same survey they would have filled out at the session. Surveys were express mailed to those who agreed along with a cover letter, $10, and a stamped return envelope. The cutoff date for accepting completed mail surveys was November 16. The response rate tables appear in the next section.

3.4.5 Response Rates

Table 3-7 presents the response rate for the telephone screener calls. At least 3 attempts were made on each record with a maximum of 10.

Table 3-7
Recruitment Response Rate[a]

	Albany	Madison	OK City	Billings	Columbus	Portland	San Diego
Starting sample	1876	1873	1500	1500	1500	1500	1500
Unusable numbers	406	669	667	706	757	873	656
Ineligible	68	18	24	36	39	49	61
Adjusted Sample	1402	1186	809	758	704	578	783
Refusals	549	265	494	590	364	370	256
Called out	778	846	248	93	265	141	458
Recruits	75	75	67	75	75	67	69
Recruit rate[b]	5.3%	6.3%	8.3%	9.9%	10.7%	11.6%	8.8%
Refusal rate[c]	39.2%	22.3%	61.1%	77.8%	51.7%	64.0%	32.7%

a. We don't provide response rate information for Denver or Miami because of the interrupted recruiting process. Recruitment started in both cities, was canceled, those agreeing initially were called back and rerecruited and then additional participants were recruited.
b. Recruit rate = recruits / adjusted sample.
c. Refusal rate = refusals / adjusted sample.

Table 3-8 shows the recruitment sites by date, the time the sessions were held, the number recruited and the number that showed at each site. Of the 62 no-shows in Miami who were called, 15 were unreachable, 9 refused, and 38 agreed to receive the mailing. Of these 38, 16 surveys were returned. This gives us 40 from Miami and a total of 383 completed surveys (including 2 from the Boulder, Colorado, pretest).

Table 3-8
Survey Implementation Facility Show Rate

Location	Date	Times	Total Recruit	Total Shows	Show Rate
Boulder	Friday 10/5	11:00 AM	5	2	40.0%
Denver	Tuesday 10/9	5:00, 6:30, 8:00	64	43	67.2%
Albany	Monday 10/15	6:00, 7:30	71	40	56.3%
Madison	Monday 10/15	6:00, 7:30	80	44	55.0%
Oklahoma City	Tuesday 10/16	6:00, 7:30	67	42	62.7%
Billings	Tuesday 10/16	6:00, 7:30	74	46	62.2%
Columbus	Wednesday 10/17	6:00, 7:30	75	48	64.0%
San Diego	Thursday 10/18	6:00, 7:30	71	39	54.9%
Portland	Thursday 10/18	6:00, 7:30	67	39	58.2%
Miami	Tuesday 10/23	6:00, 7:30	86	24	27.9%
		Totals	660	367	55.6%

CHAPTER 4
RESULTS AND ANALYSIS

4.1 SOCIODEMOGRAPHICS AND SAMPLE CHARACTERISTICS

Appendix G provides information on data quality and adjustments made to the raw data for analysis. Appendix G also provides means and standard deviations by city.

4.1.1 Sociodemographics

Table 4-1 presents summary information on the sociodemographics for the 381 attendees. Just over half (51%) of the respondents were employed full time, another 17% were employed part time, 14% were retired, 10% were homemakers, and 9% were unemployed. Eighty percent of respondents were white, 11% were black or African-American, 3% were Asian or Pacific Islander, 2% were American Indian or Alaska Native, and 3% were of another race (does not total to 100% because of rounding).

The final column of Table 4-1 shows the results of the Kruskal-Wallis test[1] of whether the samples arise from identical distributions by city. In general, it is expected that different cities have individuals with different sociodemographic characteristics and thus the findings indicated in Table 4-1 that income, age, education, and tenure in city are different between the different cities is expected. The Kruskal-Wallis test does indicate, though, that household size does not vary by city.[2]

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1. The Kruskal-Wallis test is used for nonparametric (distribution-free) independent group comparisons. Specifically it is a nonparametric test used to compare three or more independent groups of sampled data. Unlike parametric independent group tests, the Kruskal-Wallis test makes no assumptions about the distribution of the data (e.g., normality). It is an alternative to the independent group ANOVA, when the assumption of normality or equality of variance is not met. The Kruskal-Wallis test uses the ranks of the data rather than their raw values to calculate the statistic. The hypotheses for the comparison of two independent groups are:

> H_o: The samples come from identical populations
>
> H_a: They samples come from different populations

where the hypothesis makes no assumptions about the distribution of the populations. These hypotheses are also sometimes written as testing the equality of the central tendency of the populations.

2. Unless otherwise indicated, all Kruskall-Wallis tests shown in this report are comparisons of distributions between the nine different cities.

Table 4-1
Sociodemographics (n = 381)

Characteristic	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Income (2001$)	49,934.38	34,840.74	18.84 (0.02)
Age (years)	43.74	14.74	13.78 (0.09)
Education (years)	14.88	2.10	15.12 (0.06)
Gender (male = -1; female = 1)	165 males and 216 females 43% males		10.27 (0.25)
How long lived in the area (years)	19.81	17.08	18.29 (0.02)
Household size (number of people)	2.73	1.56	6.25 (0.62)

In general, we also examined intercity differences in respondent characteristics and surveys responses. We don't report all of these differences since we are primarily interested in how individuals as a whole value weather forecast information. Table 4-2 reports the cities with the maximum mean and minimum mean responses for sociodemographic characteristics for those variables indicated in Table 4-1 as arriving from different distributions.

Table 4-2
Sociodemographics — Intercity Comparisons

Characteristic	City w/Max City w/Min	Mean	SD	n
Income (2001$)	Albany	61,250.00	41,506.10	40
	Portland	37,820.51	26,327.76	39
Age (years)	Denver	48.02	13.65	43
	Miami	39.65	13.43	40
Education (years)	Denver	15.44	2.11	43
	Oklahoma City	14.16	2.40	42
How long lived in the area (years)	Columbus	24.83	16.95	48
	Miami	12.58	11.59	40

Table 4-3 shows comparisons between the sample and available census data for the nine cities for education and age distributions. As can be seen, for both high school and college graduation rates the sample reported higher education levels than the 1990 Census data indicate for all cities. As the last two columns suggest, we have somewhat lower representation among seniors than the general population, although for some cities we have a slightly higher rate of respondents over 65 (Albany and Columbus).

Table 4-3
Sociodemographics — Comparisons to Census Data

City	Population (2000)	Percent High School Graduates[a]		Percent College Graduates[a]		Percent of Over 18 that is 65 or Older	
		Population (1990)	Sample	Population (1990)	Sample	Population (1990)	Sample
Albany	294565	53%	100%	19%	45%	19%	20%
Billings	129352	54%	100%	14%	39%	18%	15%
Columbus	1068978	50%	100%	17%	50%	13%	19%
Denver	554636	54%	100%	20%	56%	14%	9%
Madison	426526	55%	93%	21%	35%	12%	5%
Miami	1623018	55%	98%	13%	48%	21%	2%
Oklahoma City	660448	50%	93%	14%	26%	16%	10%
Portland	660486	56%	100%	16%	38%	14%	10%
San Diego	2813833	51%	100%	16%	36%	15%	3%

a. The Census reports high school and college graduates for persons 25 years and over. "Percent High School Graduates" and "Percent College Graduates" are calculated as the number of high school and college graduates for persons over 25 divided by the total population. The sample percentage high school and college graduates is calculated as percentage of sample (all 18 years and older) who indicated they graduated high school or college. These percentages are thus not expected to be directly comparable.

4.1.2 Time Spent Outdoors for Job or Leisure

Individuals were also asked how much of their work time was spent working outdoors and how much of their leisure time was spent outdoors. Based on focus group discussions and the Denver pilot test, weather information appears to be more important to individuals who spend more of their time outside. This information is used to examine potential relationships between the amount of time spent outside for leisure or work and values for improved weather forecasts. Leisure time was not specifically defined in the survey and thus was left open to respondents' interpretation. As indicated in Table 4-4, on average, respondents spend 19% of their work time and 46% of their leisure time outdoors. There was no significant difference in the distributions by city of percentage of job time outdoors (Kruskal-Wallis test, $\chi^2 = 3.16$, $p = 0.92$), and there was a not quite 10% significant difference in the distributions by city of percent of leisure time outdoors (Kruskal-Wallis test, $\chi^2 = 13.27$, $p = 0.103$).

Table 4-4
Time Spent Outdoors for Job or Leisure (n = 381)

Characteristic	**Mean**	**SD**	**Kruskal-Wallis Test, χ^2 (prob H_o)**
Job time spent outside (%)	19.20	26.53	3.16 (0.92)
Leisure time spent outside (%)	46.04	20.26	13.27 (0.10)

Table 4-5 shows the cross tabulation of the individuals who spend more or less than 50% of their leisure time or job time outdoors: 162 individuals spend less than 50% of their work time *and* less than 50% of their leisure time outdoors; 42 individuals (11.2%) of the 381 respondents indicated that they spent more than 50% of their work time *and* leisure time outdoors.

We also explored determinants of the percentage of time an individual spends outdoors either on the job or for leisure using simple regression analysis (not shown here). For job time outdoors, the only significant explanatory variables were gender (males are more likely to spend more time on the job outdoors) and education (the higher the level of education the less time spent outdoors on the job). For leisure time outdoors, the only significant explanatory variables were age (younger people spent more time recreating outdoors) and “Portland” (people in Portland spend significantly less time recreating outdoors than people in San Diego, the city used as the control dummy variable for “city”).[3] As shown in Table 4-6, Miami respondents reported significantly greater time outdoors recreating (51.8% of their leisure time) than Portland respondents (38.3% of their leisure time).

3. It should be noted that when talking about individual cities our discussion is about the responses from the sample that participated from that city and cannot necessarily be generalized to the population of that city. So when we say “people in Portland spend significantly less time recreating outdoors than people in San Diego,” we mean that the respondents from Portland indicated that they spend less time recreating than respondents from San Diego indicated.

Table 4-5
Cross Tabulation of Subjects Spending 50% or More of Job Time or Leisure Time Outdoors

	Spend Less than 50% of Job Time Outdoors	Spend 50% or More of Job Time Outdoors	Row Total (percentage of total)
Spend Less than 50% of Leisure Time Outdoors	162	25	187 (49.1%)
Spend More than 50% of Leisure Time Outdoors	152	42	194 (50.9%)
Column Total (percentage of total)	314 (82.4%)	67 (17.6%)	381

Table 4-6
Percentage of Time Outside on Job and for Leisure — Intercity Comparisons

Characteristic	City w/Max City w/Min	Mean	SD	n
Percentage of Job Time Spent Outside	Oklahoma City	22.38	30.83	42
	Columbus	14.90	24.18	48
Percentage of Leisure Time Spent Outside	Miami	51.75	23.41	40
	Portland	38.33	17.93	39

Question H6 asked individuals, “On average, year round, how many hours per week do you spend traveling outside to and from work or school in a mode that could be affected by the weather?” Question H8 asked individuals, “On average, year round, how many hours per week do you spend working outside in your yard or garden, washing your car, working on the house, or other activities ‘around the house’?” The purpose of these questions was to further explore how weather may affect individuals’ activities. On average, individuals spent 12.8 hours a week traveling outside and 9.7 hours per week working outside around the house; median time spent traveling outside was 16.3 hours and median time spent working outside around the house was 12.6 hours. Hours spent outdoors traveling was not correlated with income, age, gender, education, or ethnicity. Hours spent working outside around the house was not correlated with income, age, or gender but was negatively correlated with education (higher education individuals reported spending less time working outside around the house, Pearson's correlation coefficient = -0.10, probability rho = 0 is 0.04) and ethnicity (nonwhites reported spending more time working outside around the house, Pearson's correlation coefficient = -0.16, probability rho = 0 is 0.01). There were no significant differences between the nine cities in the hours reported spent outdoors travelling or working outside around the house.

4.2 IMPORTANCE, USES, AND SOURCES OF WEATHER INFORMATION

4.2.1 Introduction to Weather Forecasts

Before eliciting information on individuals' values and preferences for weather forecast improvements, the survey explores their familiarity with, uses of, and sources of weather forecast information. While the primary function of these questions is to provide individuals with information on weather forecasting and to have them consider their uses of such information so they may better consider the valuation questions, the preliminary questions provide interesting insight into how and why households use weather forecasts. The survey begins by asking whether individuals have heard of the NWS before receiving the survey: 89.5% answered that "yes," they had heard of the weather service.

4.2.2 Importance of Weather Forecast Characteristics

Question 2 asked individuals how important different characteristics of a short-term weather forecast was to them personally (Table 4-7). As in findings in previous studies and the Denver pretest, precipitation and temperature are the most important weather forecast characteristics. Air pressure (barometric pressure) is of little interest across all cities.

Based on the Kruskal-Wallis test reported in the last column of Table 4-7, the only weather characteristics that were significantly different across the nine cites were the "amount of rain, snow, or hail" and "how cloudy it will be." As shown in Table 4-8, we compare the cities with the maximum mean response with the cities with the minimum mean response to further explore these inter-city differentials. For the most part the cities ranked the importance of the weather forecast characteristics in a similar manner with the "chance of rain, snow, or hail" as most important and "air pressure" as least important. In Columbus, individuals ranked the "amount of rain, snow, or hail" as less important than temperature features, whereas other cities considered the amount of precipitation to be more important than temperatures. Respondents in most cities considered high temperatures to be more important than low temperatures, except for those in Billings and Oklahoma City, where this was reversed. Respondents from San Diego consistently seemed least interested in weather forecast characteristics and those from Albany most concerned. It is interesting that respondents from Columbus regarded how cloudy it will be as least important compared to other cities, whereas respondents from Columbus rated temperature characteristics more important than other cities did.

Table 4-7
Importance of Weather Forecast Characteristics (Q2)

Characteristic	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Chance of rain, snow, or hail	4.30	0.82	12.44 (0.13)
Amount of rain, snow, or hail	4.02	0.96	21.73 (0.01)
High temperature	3.85	1.01	9.77 (0.28)
Low temperature	3.74	1.06	10.69 (0.22)
How windy it will be	3.28	1.08	7.60 (0.47)
How cloudy it will be	2.74	1.08	14.38 (0.07)
Air pressure	2.21	1.13	10.81 (0.21)
On a scale from 1 to 5 where 1 is “not at all important” and 5 is “very important” (min = 1; max = 5; n = 381).			

In Table 4-9 we look at how individuals rated the importance of weather forecast characteristics depending on whether they spent more or less than 50% of the job time outdoors. Fewer than 18% of the 381 individuals spend 50% or more of their on the job time outdoors. Those who spend more time outdoors on the job rated the weather forecast characteristics as more important than those who work indoors more, although there was only a significant difference for the “amount of rain, snow, or hail” and “how windy it will be.” We speculate that these two weather characteristics affect individuals’ ability to work outdoors more than other characteristics that are not significantly different by group.

One hundred and ninety-four individuals (51% of the sample) spent more than 50% of their leisure time outside. Table 4-10 compares means for importance for Question 2 forecast characteristics between those who spent more than 50% of their leisure time outside and those who didn’t. Outdoor leisurists rated all of the weather forecast characteristics as more important than those who recreate more indoors. These differences were significant for all of the forecast characteristics except for high temperature.

Table 4-8
Importance of Weather Forecast Characteristics (Q2) — Intercity Comparison

City	Characteristic	Mean	SD	n
Chance of rain, snow, or hail	Albany	4.60	0.59	40
	San Diego	3.92	1.18	39
Amount of rain, snow, or hail	Albany	4.38	0.81	40
	San Diego	3.56	1.07	39
How cloudy it will be	Albany	2.97	1.00	40
	Columbus	2.42	0.96	48
Low temperature	Columbus	4.02	1.06	48
	San Diego	3.31	1.32	39
High temperature	Columbus	4.10	0.99	48
	San Diego	3.62	1.23	39
How windy it will be	Oklahoma City	3.71	1.11	42
	San Diego	3.03	1.14	39
Air pressure	Miami	2.55	1.28	40
	Billings	1.96	0.89	46

On a scale from 1 to 5 where 1 is “not at all important” and 5 is “very important” (min = 1; max = 5).

4.2.3 Sources of Daily Weather Information

Question 3 in the survey asked respondents how often they used different sources of weather information. By far the most common source is local TV newscasts followed by commercial or public radio stations. Very few people currently appear to use the Internet or NOAA weather radio for day-to-day weather forecast information.

Table 4-9
Difference in Importance of Weather Forecast Characteristics between Outdoor and Indoor Workers

Weather Forecast Characteristic	Spend Less than 50% of Job Time Outdoors Mean (n = 314) (SD)	Spend 50% or More of Job Time Outdoors Mean (n = 67) (SD)	Wilcoxon Two-Sample Test Z (Pr > Z (2-sided))
Chance of rain, snow, or hail (Q2A)	4.28 (0.83)	4.39 (0.76)	0.91 (0.36)
Amount of rain, snow, or hail (Q2B)	3.98 (0.95)	4.19 (0.97)	2.01 (0.05)
How cloudy it will be (Q2C)	2.73 (1.10)	2.79 (0.98)	0.25 (0.80)
Low temperature (Q2D)	3.70 (1.07)	3.92 (0.96)	1.32 (0.19)
High temperature (Q2E)	3.83 (1.02)	3.91 (0.96)	0.33 (0.74)
How windy it will be (Q2F)	3.21 (1.07)	3.63 (1.08)	3.04 (0.00)
On a scale from 1 to 5 where 1 is “not at all important” and 5 is “very important” (min = 1; max = 5).			

Table 4-12 looks at intercity differences in sources for weather forecast information. As discussed elsewhere, respondents in San Diego indicated the least use of weather forecasts and thus it follows that they have the lowest level of usage for several sources of weather forecast information. Miami respondents indicated the largest usage of forecasts on cable TV and Denver respondents the least. It would be interesting to correlate this information with the availability of or cost of cable TV services in these two cities to see if this influences usage. It is also possible that given sufficient intercity information on the costs of various sources (e.g., cable, internet, newspapers) one could derive revealed preference information indicating the value of current weather forecast services. Such an effort is beyond the means of the current study.

Table 4-10
Difference in Importance of Weather Forecast Characteristics between Outdoor and Indoor Leisure Time

Weather Forecast Characteristic	Spend Less than 50% of Leisure Time Outdoors Mean (n = 187) (SD)	Spend 50% or More of Leisure Time Outdoors Mean (n = 194) (SD)	Wilcoxon Two-Sample Test Z (Pr > Z (2-sided))
Chance of rain, snow, or hail (Q2A)	4.21 (0.84)	4.39 (0.80)	2.30 (0.02)
Amount of rain, snow, or hail (Q2B)	3.93 (1.00)	4.10 (0.91)	1.71 (0.09)
How cloudy it will be (Q2C)	2.63 (1.09)	2.85 (1.06)	2.15 (0.03)
Low temperature (Q2D)	3.66 (1.04)	3.82 (1.07)	1.79 (0.07)
High temperature (Q2E)	3.78 (1.01)	3.91 (1.01)	1.42 (0.16)
How windy it will be (Q2F)	3.16 (1.11)	3.40 (1.05)	2.20 (0.03)
On a scale from 1 to 5 where 1 is “not at all important” and 5 is “very important” (min = 1; max = 5).			

To examine how individuals’ sources of weather information varies based on individual characteristics, we regressed responses to the seven sources in Question 3 on sociodemographic characteristics and individuals’ indication of the percentage of time spent outdoors for work and leisure. Table 4-8 presents summary information for these regressions. Based on F-statistics (the probability of the F-statistics is reported in the last row), it appears that sociodemographics and time outdoors has an influence on individuals’ use of various sources for these sources except for “commercial or public radio” and “NOAA weather radio.”

In general, those who spend more leisure time outdoors used all of the sources of weather information more except for NOAA weather radio and other people. Individuals who spend more of their work time outdoors use cable TV more than others. Those with higher income also use cable more, and the higher the individual’s education, the more he or she uses newspapers as a source of weather information. Older people are significantly more likely to use local TV and newspaper for their weather forecasts. Females are also more likely than males to use local TV, commercial or public radio, and other people.

Table 4-11
Sources of Daily Weather Information (Q3)

Source	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Local TV newscasts	4.05	1.15	16.97 (0.03)
Commercial or public radio	3.21	1.52	8.09 (0.43)
Cable TV stations	2.66	1.50	27.04 (0.00)
Other people	2.45	1.24	16.82 (0.03)
Newspaper	2.23	1.20	12.40 (0.13)
Internet	1.82	1.17	18.30 (0.02)
NOAA weather radio	1.20	0.71	1.68 (0.99)

1 = rarely or never; 2 = once or more a month; 3 = once or more a week; 4 = daily; 5 = twice a day; 6 = three or more times a day (n = 381).

We also ran the regression reported in Table 4-13 with a measure of weather variability as an explanatory variable, but this was not significant in explaining individuals' choice of weather information sources for any of the sources.

We explored intercity differences in the use of these sources for forecasts by running the same regressions indicated in Table 4-13 and including dummy variables for each of the cities. The excluded dummy was San Diego because this city seems to have the lowest overall use of forecasts. Without reporting all the regression statistics, respondents in Albany and Columbus were significantly more likely to use local TV forecasts; respondents in Oklahoma City were significantly more likely to use newspapers; respondents in Albany, Columbus, Denver, Madison, and Portland were all more likely to use commercial or public radio; and respondents in Columbus and Miami were more likely to use NOAA weather radio — all compared to San Diego respondents as the baseline. Location played no significant role for use of cable TV, the internet, or other people as sources of forecast information. Again, although not the focus of this research, it would be interesting to further explore why different cities indicated different levels

Table 4-12
Intercity Comparison of Sources of Daily Weather Information (Q3)

Source	City	Mean	SD	n
Local TV newscasts	Albany	4.40	1.24	40
	Madison	3.61	1.22	44
Cable TV stations	Miami	2.98	1.40	40
	Denver	2.26	1.36	43
Newspaper	Columbus	2.69	1.21	48
	Oklahoma City	1.69	0.98	42
Commercial or public radio	Albany	3.65	1.73	40
	San Diego	2.74	1.62	39
NOAA weather radio	Columbus	1.46	1.11	48
	San Diego	1.03	0.16	39
Internet	Madison	2.16	1.29	44
	Billings	1.50	0.96	46
Other people	Oklahoma City	2.60	1.23	42
	San Diego	2.26	1.21	39

1 = rarely or never; 2 = once or more a month; 3 = once or more a week; 4 = daily; 5 = twice a day; 6 = three or more times a day.

of use for some of these sources and not for others. While this would be of interest to companies marketing weather forecast information, it could also lead to a better understanding of how people prefer to receive weather information and thus ways of improving the transmission of this information.

4.2.4 Use of Weather Forecasts in Planning

Of importance to understanding individuals' values for weather information is how they can and do use weather information in making behavioral decisions. If they have no flexibility to respond to weather information, then improved information may have little value, however important they perceive it to be. Question 4 asked individuals how often do they use weather forecasts to help plan for several activities. Table 4-14 shows mean responses in order of decreasing frequency.

Table 4-13
Ordinary Least Squares Regression of Sources of Weather Forecast Sources

	Dependent Variables: Frequency of Source (Q3)						
	Local TV Newscasts (Q3A)	**(Cable) TV Stations (Q3B)**	**Newspaper (Q3C)**	**Commercial or Public Radio (Q3D)**	**NOAA Weather Radio (Q3E)**	**Internet (Q3F)**	**Other People (Q3G)**
	Parameter Est. (SE)	Parameter Est. (SE)	Parameter Est. (SE)	Parameter Est. (SE)	Parameter Est. (SE)	Parameter Est. (SE)	Parameter Est. (SE)
Intercept	3.445 (0.469)***	2.307 (0.632)***	-0.436 (0.481)	2.615 (0.646)***	1.014 (0.302)***	1.561 (0.483)***	2.828 (0.507)***
Gender	0.237 (0.059)***	-0.044 (0.079)	0.015 (0.060)	0.136 (0.081)*	0.037 (0.038)	-0.175 (0.060)	0.211 (0.063)***
Age (years)	0.018 (0.004)***	0.006 (0.005)	0.025 (0.004)***	0.007 (0.005)	0.004 (0.003)	-0.015 (0.004)	-0.022 (0.004)
Income (1,000s)	0.001 (0.002)	0.005 (0.002)*	0.001 (0.002)	0.002 (0.002)	0.000 (0.001)	0.002 (0.002)	-0.001 (0.002)
Education (years)	-0.043 (0.09)	-0.040 (0.040)	0.075 (0.030)**	-0.015 (0.040)	-0.008 (0.019)	0.038 (0.030)	0.029 (0.032)
Percent time work outdoors	0.002 (0.002)	0.006 (0.003)**	0.003 (0.002)	0.001 (0.003)	0.002 (0.001)	-0.002 (0.002)	0.002 (0.002)
Percent time leisure outdoors	0.008 (0.003)***	0.007 (0.004)*	0.007 (0.003)**	0.008 (0.004)**	0.002 (0.002)	0.007 (0.003)**	0.003 (0.003)
ADJRSQ	0.088	0.025	0.123	0.008	-0.002	0.065	0.092
ProbF	0.000	0.016	0.000	0.176	0.514	0.000	0.000

*, **, *** indicates significance at the 10%, 5%, and 1% level, respectively (n = 381).

Dressing yourself or your children for the day ranked highest (based on mean scores), suggesting that individuals can and do use weather forecasts for these activities. Activities related to work ranked lowest, perhaps because individuals have less flexibility to make behavioral adjustments to forecast weather for these activities.

Table 4-15 shows the cities with the maximum and minimum means for Question 4 responses for the variables indicated as significantly different by the Kruskal-Wallis test in Table 4-14.

Table 4-14
How Often Do You Use Weather Forecasts in Planning for Each of the Activities? (Q4)

Activity	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Dressing yourself or your children for the day	3.97	1.13	38.16 (0.00)
Planning for the weekend	3.76	1.11	17.91 (0.02)
Vacation or travel	3.61	1.19	14.16 (0.08)
Social activities	3.21	1.13	9.57 (0.30)
House or yardwork	3.11	1.24	10.85 (0.21)
How to get to work, school, or the store	2.88	1.31	12.14 (0.15)
Job or business	2.76	1.41	18.90 (0.02)

Where 1 = "never"; 2 = "rarely"; 3 = "half the time"; 4 = "often"; 5 = "most of the time" (n = 381).

Table 4-15
Intercity Differences in Uses of Forecast Information (Q4)

Use	City	Mean	SD	n
Dress for the day (Q4A)	Billings	4.35	0.97	46
	San Diego	3.08	1.33	39
Job or business (Q4C)	Oklahoma City	3.17	1.56	42
	Columbus	2.25	1.12	48
Vacation or travel (Q4F)	Miami	4.17	1.11	40
	Columbus	3.46	1.22	48
Planning for the weekend (Q4G)	Miami	4.25	1.01	40
	San Diego	3.18	1.23	39

Where 1 = "never"; 2 = "rarely"; 3 = "half the time"; 4 = "often"; 5 = "most of the time."

Nearly all the activity categories in Question 4 are positively and significantly correlated with the question in the sociodemographics question asking what percentage of time is spent working outside and what percentage of time is spent in leisure outside — those spending more work or leisure time outside indicating that they use forecasts more for planning these activities.
Table 4-16 compares mean scores to Question 4 using the same splits between outdoor and indoor workers described above (see Table 4-5). Both groups use weather forecasts most often for planning for how to "dress for the day." The significant difference between these two groups is that forecasts for planning for "job or business" is used significantly more often by those who work outdoors more than 50% of time than those who don't and those who work outdoors more also use forecast more for planning for "vacation or travel." The use of forecasts for job planning for outdoor workers ranks higher than other uses such as social activities or travel to work plans, whereas it is ranked lowest by the indoor workers.

Table 4-16
Difference in Use of Weather Forecast for Planning between Outdoor and Indoor Workers
(shown in descending order of importance for indoor workers)

Planning	Spend Less than 50% of Job Time Outdoors (n = 314) Mean (SD)	Spend 50% or More of Job Time Outdoors (n = 67) Mean (SD)	Wilcoxon Two-Sample Test Z (Pr > Z (2-sided))
Dress for the day (Q4A)	3.933 (1.141)	4.119 (1.080)	1.315 (0.189)
Planning for the weekend (Q4G)	3.720 (1.118)	3.940 (1.071)	1.523 (0.129)
Vacation or travel (Q4F)	3.536 (1.185)	3.940 (1.179)	2.678 (0.008)
Social activities (Q4E)	3.183 (1.145)	3.320 (1.061)	0.875 (0.382)
House or yardwork (Q4D)	3.061 (1.233)	3.315 (1.233)	1.475 (0.141)
How to get to work/ school/store (Q4B)	2.828 (1.307)	3.104 (1.327)	1.533 (0.126)
Job or business (Q4C)	2.509 (1.321)	3.940 (1.205)	7.307 (0.000)
Where 1 = "never"; 2 = "rarely"; 3 = "half the time"; 4 = "often"; 5 = "most of the time."			

Table 4-17 makes a similar comparison between indoor and outdoor leisurists. Whereas indoor leisurists use forecasts most for planning for how to “dress for the day,” outdoor leisurists use forecasts more often “planning for the weekend” than any other activity. Overall, outdoor leisurists use forecasts for all of these activities significantly more than indoor leisurists.

Table 4-17
Difference in Use of Weather Forecast for Planning between Outdoor and Indoor Leisure Planning
(shown in descending order of importance for indoor leisurists)

Planning	Spend Less than 50% of Leisure Time Outdoors (n = 187) Mean (SD)	Spend 50% or More of Leisure Time Outdoors (n = 194) Mean (SD)	Wilcoxon Two-Sample Test Z (Pr > Z (2-sided))
Dress for the day (Q4A)	3.856 (1.180)	4.072 (1.075)	1.771 (0.077)
Planning for the weekend (Q4G)	3.412 (1.144)	4.093 (0.972)	5.980 (0.000)
Vacation or travel (Q4F)	3.310 (1.182)	3.893 (1.134)	4.844 (0.000)
Social activities (Q4E)	2.973 (1.166)	3.432 (1.050)	3.970 (0.000)
House or yardwork (Q4D)	2.941 (1.249)	3.263 (1.204)	2.502 (0.013)
How to get to work/school/store (Q4B)	2.727 (1.264)	3.021 (1.346)	2.081 (0.038)
Job or business (Q4C)	2.455 (1.349)	3.055 (1.408)	4.193 (0.000)
Where 1 = “never”; 2 = “rarely”; 3 = “half the time”; 4 = “often”; 5 = “most of the time.”			

The differences in the importance of forecast characteristics and the use of forecasts for planning various activities between those who work more or less outside and between those who spend more or less leisure time outdoors suggest that values may differ between these groups in a systematic fashion. These issues are explored further in the analysis of the valuation questions in Chapter 5.

To further understand individuals' behavioral response to weather information, we performed a factor analysis on the responses to Question 4. Factor analysis examines correlations between responses to multiple questions to see if there is a relationship between some of the questions that can be explained by a smaller number of "factors." If two or more questions are related in such a way as to be providing similar information, they are said to "load" on that factor. If multiple factors are identified, the data are "rotated" to separate the factors as much as possible. Factor scores can then be used to generate single numbers for each respondent for each factor. In this manner, answers to seven questions that generated two factors can be reduced to two new numbers representing individuals' responses to those seven questions. In this manner, factor analysis is considered a data reduction method. For Question 4 we retained two factors (Table 4-18).[4] Table 4-18 shows the factor loadings where loadings greater than 0.40 in absolute value are used to identify which scales belong to which factor. Factor 1, which we label "discretionary time use of forecasts," comprises three scales related to social and discretionary activities. Factor 2, "nondiscretionary time use of forecasts," comprises the other four scales, ones for which individuals seem to have a lesser degree of behavioral flexibility.

Table 4-18
Rotated Factor Pattern (Q4)

Description	Factor 1: Discretionary Time Use of Forecasts	Factor 2: Nondiscretionary Time Use of Forecasts
Planning for weekend (Q4G)	**0.67**	0.40
Vacation or travel (Q4F)	**0.64**	0.22
Social activities (Q4E)	**0.63**	0.39
Job or business (Q4C)	0.32	**0.58**
House or yardwork (Q4D)	0.32	**0.42**
Dress for the day (Q4A)	0.25	**0.51**
How to get to work/school/store (Q4B)	0.22	**0.60**

Bold indicates the loading of a scale on a factor (absolute value > 0.40) (n = 381).

4. We used an orthogonal varimax rotation to obtain a final solution (Hatcher, 1994).

Undertaking factor analysis with two separate groups and splitting the sample into those who work outside more than 50% of the time and those who don't work outdoors more than 50% of the time does not appreciably change the structure of the factor analysis results. When split into two groups, the variable "house or yardwork" does not load on any factor for the group that spends less than 50% of their time working indoors. The other variables load on the same factors as indicated in Table 4-18. Undertaking the factor analysis and splitting the sample into the two groups by those who work spend 50% or more of their leisure time outdoors and those who spend less than 50% of their leisure time outdoors doesn't change the factor loadings for the outdoor leisurists. For indoor leisurists, though, the "job or business" and "house or yardwork" variables now load on the second factor rather than the first, suggesting a somewhat different approach in using forecasts for planning their activities. To maintain consistency in the creation of factor scores across groups, we use the factor analysis of the entire sample to generate factor scores.

Standardized scoring coefficients were generated from the rotated factor pattern and used to calculate factor scores for each individual. Since the factor scores represent composite measures for the factors that underlie the answers to the questions asked in Question 4, they reduce these seven answers to two measures, one for each relevant factor. Thus an individual who often used forecasts for planning social activities, vacations, or weekend activities would have a higher factor score than someone who did not use forecasts for these discretionary activities. Factor scores generally are generated with roughly a mean zero normal distribution. These two factor scores are used in the analysis of the choice questions and the willingness to pay for weather forecast improvements.

4.2.5 Adequacy of Current and Importance of Improving Weather Information Attributes

Individuals were then presented with information on the NWS and the technology and processes involved in generating and communicating weather forecast information. Potential approaches to improving forecast quality were presented and four forecast characteristics were introduced and discussed. Individuals were informed of the current levels of the forecast characteristics and potential levels if improvements were undertaken (see Table 3-1). Questions 5, 7, 9, and 11 asked, "Under normal weather conditions, how adequate do you think that . . ." the current level is for each of the four attributes? Table 4-19 shows individuals' ratings of the adequacy of current forecast attribute levels in descending order of average level of adequacy. Individuals indicated that the current frequency of updates is the most adequate of the four attributes and that geographic detail is least adequate. The only attribute that appeared to differ in terms of the responses by city is the adequacy of 5-day forecasts. On average, respondents in Columbus rated 5-day forecasts 3.13 on the 5-point scale, whereas respondents in Billings rated the adequacy of 5-day forecasts significantly lower at 2.58 ($t = 3.13$, which is significantly different at the 1% level).

Table 4-19
Adequacy of Current Levels of Forecast Attributes (Q5, Q7, Q9, Q11)
(shown in descending order of adequacy)

Attribute	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Adequacy of updates 4 times a day (Q5)	3.30	0.68	8.71 (0.37)
Adequacy of weather forecasts 5 days in advance (Q9)	2.89	0.84	20.67 (0.01)
Adequacy of 80% correctness of one-day forecasts (Q7)	2.88	0.81	10.56 (0.23)
Adequacy of geography detail to 30 miles by 30 miles (Q11)	2.74	0.88	11.28 (0.19)

Where 1 = “much less than adequate”; 2 = “less than adequate”; 3 = “about right”; 4 = “more than adequate”; 5 = “much more than adequate”; n = 381.

Questions 5, 8, 10, and 12 elicited individuals’ ratings of the usefulness of the different levels of potential weather forecast improvements. Table 4-20 lists the mean values for the “usefulness” of different levels of weather forecast improvement in descending order of usefulness. Improving the accuracy of one-day forecasts to 95% (instead of the current 80%) was considered the most useful potential improvement, followed by improvements in one-day forecasts to 90%. Overall improvements to one-day forecasts are followed by improvements to multiday forecasts, geographic detail, and frequency of forecasts. It should be noted that the rating of the importance of improving the frequency of forecasts decreases as the frequency of updates increases. This response is similar to findings in focus groups and one-on-one interviews, where the current level of the frequency of updates was considered adequate. For many individuals it appeared that they currently access weather forecasts three or fewer times a day and thus may perceive little use in more frequent updates by the NWS.

In a similar vein to the usefulness question, Question 37 asked individuals how important the various forecast characteristics (or attributes) were in making their choices between alternatives. Table 4-21 presents the relative rankings based on mean scores for Q37. Since one of the attributes in the choice questions was the cost to individuals for the improvement programs, cost is now ranked relative to the forecast attributes. For the forecast attributes, the same relative ranking is found with one-day forecasts followed by improving multiday forecasts, improving geographic detail, and increasing frequency of updates.

Table 4-20
Importance of Improving Weather Information Attributes (Q6, 8, 10, and 12)

Question	Attribute	Mean	SD
Q8C	Accuracy of one day forecasts (95% correct)	3.81	1.22
Q8B	Accuracy of one day forecasts (90% correct)	3.40	1.04
Q10C	Accuracy of multiday forecasts (14 days)	3.35	1.34
Q10B	Accuracy of multiday forecasts (10 days)	3.29	1.12
Q10A	Accuracy of multiday forecasts (7 days)	3.29	0.98
Q12C	Geographic detail (3 miles)	3.21	1.40
Q12B	Geographic detail (7 miles)	3.14	1.11
Q12A	Geographic detail (15 miles)	3.08	1.00
Q8A	Accuracy of one day forecasts (85% correct)	3.05	0.98
Q6A	Frequency of updates (6 times/day)	2.61	0.99
Q6B	Frequency of updates (9 times/day)	2.08	1.04
Q6C	Frequency of updates (12 times/day)	1.96	1.23
On a scale from 1 to 5 where 1 is “not at all useful” and 5 is “very useful”; n = 381.			

Table 4-21
Importance of Improving Weather Information Attributes
in Making Choices between Alternatives (Q37)

Attribute	Mean	SD
Accuracy of one-day forecasts	3.81	1.15
Accuracy of multiday forecasts	3.71	1.13
Yearly cost to your household	3.64	1.27
Geographic detail	3.27	1.26
Frequency of updated forecasts	2.53	1.25
On a scale from 1 to 5 where 1 is “not at all important” and 5 is “extremely important”; n = 381.		

4.2.6 Conclusions

Responses to parts of almost all of the various perceptions, sources, and uses questions differed in some manner based on where the individual lived and the amount of time he or she spends out of doors for either work or leisure. As would be expected, for those who work or recreate outdoors, the weather forecast plays a larger role in their decision making. Individual sociodemographic characteristics such as age, income, gender, and education also played a role in individuals' perceptions, sources, and uses of weather forecasts.

In general, the characteristics of a forecast that individuals felt were most important are precipitation and temperature. Winds, clouds, and air pressure are of less interest in general, although forecasts for winds are of significantly more interest to those who work outdoors.

Local TV and radio are the primary sources for most individuals for their day-to-day weather forecasts. Internet and NOAA weather radio are used infrequently, if ever, by the majority of respondents. The degree to which different individuals use different sources is closely related to various sociodemographic characteristics of the individual such as age, income, gender, and education, as well as how much time is spent outdoors for work or leisure.

Forecasts are used by individuals most for decisions over which they have some flexibility such as what to wear on any given day or what to do on the weekend. Forecasts are not used as much for decision making where the individual is more constrained by such things as jobs or business or transportation to work, school, or the store.

In general, individuals' uses of forecasts and perceptions of forecasts were related to their location as well. For instance, individuals in San Diego rated forecast variables lower than individuals in other cities on several scales such as importance of forecasts and use of forecast information. This is expected where regional differences in climate make it easier for an individual in San Diego to predict the next day's weather himself than it may be for an individual in Billings or Denver. In general the weather in San Diego is also "nicer" and thus has less potential for significantly affecting an individual's activities at work or at leisure.

Individuals perceive that the current frequency of forecast updates is adequate at least for day-to-day forecasts. Less adequate, in descending order, are weather forecasts 5 days in advance, the correctness of one-day forecasts, and the geographic detail of forecasts. This correlates with individuals' statements of the importance of improving weather forecasts, where they are most interested in improvements in one-day and multiday forecasts, somewhat interested in improvements in geographic detail, and uninterested in increased frequency of forecast updates.

4.3 SEVERE WEATHER

The final set of questions in the survey explored preliminary issues related to severe weather. Question O3 asked, "For the area where you live and work, how important is it to you personally to receive weather information about each of the severe weather events listed below?" followed by a listing of 13 weather related events. Table 4-22 lists mean responses in descending order of importance. We report the actual number of responses to these questions because we did not replace missing responses. Averaged across the nine cities, tornadoes ranked as the most important item for these respondents to receive weather forecast information on in the event of severe weather and hurricanes ranked as least important. As can be seen, though, the Kruskal-Wallis test indicates that there are significantly different responses to these questions between the nine different cities for every severe weather category except "extreme heat."

Table 4-22
Local Importance of Severe Weather (Question O3)

Severe Weather Item	N	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Tornadoes (O3G)	368	4.261	1.299	53.48 (0.00)
Snow or ice storms (O3K)	371	4.178	1.334	77.19 (0.00)
Extreme cold (O3C)	378	4.153	1.180	37.94 (0.00)
Wind storms (O3H)	371	3.989	1.155	21.58 (0.01)
Thunderstorms (O3A)	381	3.976	1.150	39.66 (0.00)
Hail (O3L)	371	3.933	1.245	43.44 (0.00)
Extreme heat (O3B)	381	3.924	1.134	3.56 (0.90)
Lightning (O3E)	377	3.690	1.170	15.87 (0.04)
Fire danger/drought (O3I)	372	3.667	1.349	42.42 (0.00)
Flash floods (O3J)	366	3.642	1.387	28.50 (0.00)
Air quality (O3M)	374	3.433	1.283	16.28 (0.04)
Fog or low clouds (O3D)	378	3.119	1.207	25.90 (0.00)
Hurricanes (O3F)	360	2.992	1.798	84.05 (0.00)

On a scale from 1 to 5 where 1 is "not at all important" and 5 is "very important" (min = 1; max = 5).

Table 4-23 shows the rankings by city based on the mean level of importance for each city. The highest rated severe weather item is bolded and shaded. Respondents in all of the cities except Miami and San Diego rated information about snow or ice storms first or second. As could be expected, Miami and San Diego respondents rated snow or ice storms as being of least importance. Miami respondents rated information about hurricanes as most important whereas most of the other cities rated this characteristic of lesser importance (twelfth or thirteenth). Albany respondents rated hurricane information sixth, which may be expected since historically states along the Atlantic coast are subject to the effects of hurricanes (Pielke and Peilke, 1997).

As may be expected, Oklahoma City respondents rated information about tornadoes as being of greatest importance. Madison respondents also rated tornadoes as being of greatest importance. Although not commonly thought of as lying in "Tornado Alley," Wisconsin does have an average of 20 tornadoes a year and in 2001 experienced 12 tornadoes (http://www.crh.noaa.gov/mkx/climate/2001arch/2001tornadoes.htm accessed 01/15/02).[5]

Other ratings seemed to follow reasonable patterns as well: respondents from more northern cities were more interested in information about cold (e.g., Albany, Billings, Portland) and those from southern cities were more interested in information about extreme heat (e.g., Miami); respondents from inland cities rated hurricane information as having minimal importance; fog or low clouds rated fairly low amongst respondents from most cities except San Diego, which experiences sea fogs (Leipper, 1994). Air quality is considered of lesser importance, except by respondents in Portland and San Diego, where it ranked fourth in both cities. San Diego respondents rated fires/drought as most important, which is consistent with the climate history of Southern California. Historically, San Diego has experienced severe droughts, including those in 1863-1865 and 1877 and major fires in 1872, 1985, and 1996 (http://edweb.sdsu.edu/sdhs/timeline/timeline.htm accessed 01/15/02).

Table 4-24 presents OLS regression analysis of individuals' ratings for each of the Question O3 categories. For most types of extreme weather, females rated weather forecast information on these events as more important than males did. The only types of severe weather information related to the amount of time an individual spends outdoors on the job were information on fog or low clouds and on flash floods. Severe weather information on thunderstorms, extreme heat, and lightning are of increasing importance as an individual spends more of his or her time outdoors for leisure. The importance of information on severe weather is directly related to both the individuals' use of weather forecast information for discretionary (planning for weekend, vacation or travel, social activities) and nondiscretionary (job or business, house or yardwork, how to dress for the day, and how to get to work/school/store) activities as derived in Table 4-18.

5. On April 11-12, 1965, Wisconsin was subject to the "Palm Sunday Outbreak" of tornadoes that spawned 51 tornadoes in the Midwest/Great Lakes states, including 6 in Wisconsin. Overall, this outbreak involved 258 deaths, 3 of which occurred in Wisconsin, along with 65 injuries in Wisconsin. On June 7-8, 1984, Wisconsin also experienced 9 tornadoes that caused 9 deaths in Barneveld and 202 injuries in the state. (http://www.crh.noaa.gov/mkx/climate/torout.htm accessed 01/15/02)

Table 4-23
Rankings by City of Local Importance of Severe Weather (Question O3)

Label	City (n^a)	Albany (40)	Billings (46)	Columbus (48)	Denver (43)	Miami (40)	Madison (44)	Oklahoma City (42)	Portland (39)	San Diego (39)
Thunderstorms (O3A)		8	5	6	6	3	4	3	9	7
Extreme heat (O3B)		9	7	7	7	7	5	7	7	2
Extreme cold (O3C)		3	3	3	4	10	3	5	2	6
Fog or low clouds (O3D)		13	12	10	12	12	9	12	13	3
Lightning (O3E)		12	9	8	8	6	8	8	10	8
Hurricanes (O3F)		6	13	13	13	**1**	13	13	12	9
Tornadoes (O3G)		2	4	2	2	2	**1**	**1**	11	11
Wind storms (O3H)		5	8	4	5	5	6	4	3	10
Fire danger/drought (O3I)		7	6	11	9	8	12	10	8	**1**
Flash floods (O3J)		10	10	9	10	4	11	9	5	5
Snow or ice storms (O3K)		**1**	2	**1**	**1**	13	2	2	**1**	13
Hail (O3L)		4	**1**	5	3	11	7	6	6	12
Air quality (O3M)		11	11	12	11	9	10	11	4	4

a. The actual number of observations for each statistic varies because of “don’t know” responses and item nonresponses.

Table 4-24
OLS Regression on Local Importance of Severe Weather (Question O3)

	Thunder-storms (O3A)	Extreme Heat (O3B)	Extreme Cold (O3C)	Fog or Low Clouds (O3D)	Lightning (O3E)	Hurricanes (O3F)	Tornadoes (O3G)	Wind Storms (O3H)	Fire Danger/ Drought (O3I)	Flash Floods (O3J)	Snow or Ice Storms (O3K)	Hail (O3L)	Air Quality (O3M)
Intercept	3.637 ***	3.604 ***	4.033 ***	2.943 ***	3.400 ***	2.691 ***	4.032 ***	3.743 ***	3.424 ***	3.446 ***	4.305 ***	3.919 ***	3.337 ***
Gender	0.096 *	0.081	0.204 ***	0.080	0.113 **	0.031	0.141 **	0.165 ***	0.178 **	0.102	0.214 ***	0.158 **	0.069
Average percent of on-the-job time spent outdoors	0.002	0.001	0.000	0.007 ***	0.002	0.005	0.000	0.002	0.002	0.005 *	-0.001	-0.003	0.002
Average percent of leisure time spent outdoors	0.006 **	0.006 **	0.002	0.001	0.005 *	0.004	0.004	0.004	0.004	0.002	-0.003	0.001	0.001
Discretionary use factor	0.321 ***	0.205 ***	0.205 **	0.274 ***	0.331 ***	0.402 ***	0.189 *	0.368 ***	0.348 ***	0.415 ***	0.072	0.156 *	0.103
Nondiscretionary use factor	0.393 ***	0.465 ***	0.490 ***	0.304 ***	0.379 ***	0.044	0.302 ***	0.352 ***	0.166	0.243 **	0.588 ***	0.591 ***	0.213 **
Adjusted R-sq.	0.211	0.189	0.197	0.137	0.199	0.037	0.079	0.215	0.095	0.121	0.147	0.184	0.023

*, **, *** indicates significance at the 10%, 5%, and 1% level, respectively (n varies by regression).

Table 4-25 repeats these regressions adding in dummy variables for the nine cities. San Diego is the excluded city for the dummy variables and thus significance of the dummy variables is in relation to the importance of severe weather forecasts for San Diegans. For instance, as expected, forecasts for cold weather are significantly less important for respondents from San Diego than for respondents from every other city except Miami. Fog forecasts are also significantly more important for respondents from San Diego than for any other city. For respondents from Miami, severe weather forecasts for hurricanes (Question O3F) are significantly more important than they are for respondents from San Diego. For respondents of all other cities, hurricane forecasts are either insignificant or significantly less important than for residents of San Diego. As indicated by the negative coefficients on all dummy variables in the regression on Question O3I, fire danger and drought forecasts are significantly more important to respondents of every other city except Billings.

Individuals were then told that “watches and warnings usually deal with expected severe weather events a few minutes to 12 hours in advance (depending on the type of weather event)” and asked their perceptions of the accuracy of watches and warnings for the same set of severe weather events “where you live.” Table 4-26 lists perceived accuracy in descending order based on mean scores. These rankings could be compared to statistical measures of forecast accuracy for these various phenomena to determine where the public perception of forecast quality differs most from forecasters’ measures of forecast quality. Because quality is inherently multidimensional, exploring potential differences between laypeople’s and experts’ perceptions of forecast quality would require more in-depth assessments. Overall respondents felt that watches and warnings for extreme temperatures were most accurate and those for air quality, hail, and fog were least accurate.

Of these 13 items, only 6 were perceived to be significantly different by individuals in the nine cities. For the six severe weather events where significant differences are indicated by the Kruskal-Wallis test in Table 4-25, Table 4-27 shows mean importance rating by city. The city with the highest mean rating is bolded.

For most of these categories, it appears that the city or cities that may have the most experience with these phenomena rated perceived forecast accuracy high or highest.[6] For instance, Miami respondents rated the accuracy of hurricane forecasts higher than any other city and Oklahoma City respondents rated the accuracy of tornado forecasts higher than any other city. It is interesting to note, though, that the perceived accuracy of fire/drought forecasts, which were considered of most concern to individuals in San Diego, is rated fairly low compared to several of the other cities where it was not as large of a concern.

6. For some weather events the question probably is not relevant: for instance, hurricane forecasts have little relevance “for where you live” if you live in Denver or Billings.

Table 4-25
OLS Regression on Local Importance of Severe Weather (Question O3)
(with city dummy variables)

Dependent	Thunder-storms (O3A)	Extreme Heat (O3B)	Extreme Cold (O3C)	Fog or Low Clouds (O3D)	Lightning (O3E)	Hurricanes (O3F)	Tornadoes (O3G)	Wind Storms (O3H)	Fire Danger/ Drought (O3I)	Flash Floods (O3J)	Snow or Ice Storms (O3K)	Hail (O3L)	Air Quality (O3M)
Intercept	3.21 ***	3.87 ***	3.41 ***	3.91 ***	3.16 ***	3.19 ***	2.93 ***	3.06 ***	4.24 ***	3.57 ***	2.92 ***	3.05 ***	3.81 ***
Gender	0.10 *	0.09	0.17 ***	0.11 *	0.12 **	0.09	0.15 **	0.15 ***	0.19 ***	0.12 *	0.15 ***	0.12 **	0.09
Average percent of on-the-job time spent outdoors	0.00	0.00	0.00	0.01 ***	0.00	0.00	0.00	0.00	0.00	0.00 *	0.00	0.00	0.00
Average percent of leisure time spent outdoors	0.01 **	0.01 **	0.00	0.00	0.01 *	0.00	0.00	0.00 *	0.00	0.00	0.00	0.00	0.00
Discretionary use factor	0.29 ***	0.20 **	0.29 ***	0.28 ***	0.30 ***	0.22 *	0.18 **	0.35 ***	0.32 ***	0.33 ***	0.23 ***	0.22 ***	0.08
Nondiscretionary use factor	0.36 ***	0.49 ***	0.37 ***	0.39 ***	0.37 ***	0.22	0.15	0.31 ***	0.28 ***	0.32 ***	0.35 ***	0.46 ***	0.28 ***
City dummy variables (San Diego missing dummy)													
Albany	0.30	-0.39	0.79 ***	-1.21 ***	0.02	0.58	1.50 ***	0.65 ***	-0.54 *	-0.10	1.72 ***	1.00 ***	-0.40
Billings	0.52 **	-0.19	0.75 ***	-1.52 ***	0.20	-1.15 ***	0.92 ***	0.61 ***	-0.43	-0.23	1.44 ***	1.28 ***	-0.84 ***
Columbus	0.45 **	-0.19	0.80 ***	-0.66 ***	0.34	-0.47	1.47 ***	0.88 ***	-1.16 ***	-0.31	1.71 ***	0.97 ***	-0.64 **
Denver	0.28	-0.39 *	0.62 ***	-1.18 ***	0.31	-0.82 **	1.33 ***	0.54 **	-0.80 ***	-0.21	1.57 ***	1.17 ***	-0.49 *

Table 4-25
OLS Regression on Local Importance of Severe Weather (Question O3)
(with city dummy variables) (cont.)

Dependent	Thunder-storms (O3A)	Extreme Heat (O3B)	Extreme Cold (O3C)	Fog or Low Clouds (O3D)	Lightning (O3E)	Hurricanes (O3F)	Tornadoes (O3G)	Wind Storms (O3H)	Fire Danger/ Drought (O3I)	Flash Floods (O3J)	Snow or Ice Storms (O3K)	Hail (O3L)	Air Quality (O3M)
Miami	0.79 ***	-0.24	-0.33	-1.10 ***	0.49 **	1.52 ***	1.35 ***	0.68 ***	-0.62 **	0.57 *	-0.47 **	0.05	-0.34
Madison	0.72 ***	-0.18	0.94 ***	-0.94 ***	0.22	-1.58 ***	1.48 ***	0.60 ***	-1.84 ***	-0.77 ***	1.63 ***	0.73 ***	-0.81 ***
Oklahoma City	0.80 ***	-0.15	0.63 ***	-0.91 ***	0.49 **	-0.55	1.75 ***	0.97 ***	-0.59 **	0.18	1.49 ***	1.05 ***	-0.63 **
Portland	0.05	-0.42 *	0.71 ***	-0.97 ***	-0.01	-0.16	0.23	0.80 ***	-0.74 ***	0.06	1.64 ***	0.68 ***	-0.02
Adjusted R-squared	0.25	0.18	0.28	0.23	0.21	0.24	0.24	0.25	0.21	0.16	0.43	0.28	0.05

Table 4-26
Perceived Accuracy of Watches and Warnings for Severe Weather

Watches and Warnings	N	Mean	SD	Kruskal-Wallis Test, χ^2 (prob H_o)
Extreme heat (O4B)	371	4.22	0.74	7.49 (0.48)
Extreme cold (O4C)	362	4.19	0.84	10.63 (0.22)
Thunderstorms (O4A)	371	3.97	0.73	19.58 (0.01)
Fire danger/drought (O4I)	328	3.94	0.88	17.58 (0.02)
Snow or ice storms (O4K)	341	3.84	0.92	9.73 (0.28)
Tornadoes (O4G)	328	3.82	0.98	22.22 (0.00)
Wind storms (O4H)	336	3.79	0.89	7.23 (0.51)
Lightning (O4E)	344	3.75	0.86	17.78 (0.02)
Hurricanes (O4F)	246	3.74	1.29	23.10 (0.00)
Flash floods (O4J)	316	3.67	0.98	21.64 (0.01)
Air quality (O4M)	294	3.67	0.97	6.61 (0.58)
Fog or low clouds (O4D)	334	3.66	0.84	6.49 (0.59)
Hail (O4L)	339	3.55	0.97	9.07 (0.34)

On a scale from 1 to 5 where 1 is "not at all accurate" and 5 is "extremely accurate."

Table 4-27
Perceived Accuracy of Watches and Warnings for Severe Weather by City

Label	City (n)	Albany (40)	Billings (46)	Columbus (48)	Denver (43)	Miami (40)	Madison (44)	Oklahoma City (42)	Portland (39)	San Diego (39)
O4A Thunderstorms		4.03	4.13	4.02	3.93	4.03	4.05	**4.17**	3.63	3.67
O4E Lightning		3.64	3.95	3.70	3.83	3.95	3.69	**3.98**	3.46	3.48
O4F Hurricanes		4.31	3.00	3.81	3.55	**4.33**	3.06	3.56	3.64	3.76
O4G Tornadoes		3.76	3.81	3.84	3.63	4.03	3.90	**4.26**	3.14	3.58
O4I Fire/Drought		3.97	**4.36**	3.76	3.90	4.03	3.74	3.73	3.97	3.86
O4J Flash Floods		**4.16**	3.59	3.73	3.49	3.89	3.69	3.51	3.15	3.71

On a scale from 1 to 5 where 1 is “not at all accurate” and 5 is “extremely accurate.”
The bolded cell on each row indicates the city that rated forecast accuracy highest for that severe weather phenomenon.

Following Question O4, individuals were asked in an open-ended format, “Of all of the possible severe or extreme weather conditions listed in the question above, which one event type would you most like to see more effort put into to improve forecasting abilities?” Table 4-28 shows the coding of the written responses to this question. Some individuals listed up to five different concepts or responses to this question and we thus coded five variables for this question. Improving the accuracy of tornado forecasts is of primary concern to the group as a whole, followed by snow storms, thunderstorms, and hurricanes.

Table 4-28
Importance to Improve Watches and Warnings for Severe Weather[a]

Wording	O5A	O5B	O5C	O5D	O5E
Tornado	101	11	3	1	
Snow storms	96	11	4		
Thunderstorms	29	4	2		1
Hurricane	28	3			
Air quality	16				
Extreme cold	13	5			
Lightning	11	2		1	
Extreme heat	9	5	1		
Hail	9	1		1	1
Fog	8				
Flash floods	7	4	6		
Wind storms	7	4	1	1	
Fire danger	7				
None (written in)	5				
Ice storms	4	80	6	2	
Rain	4	2		1	
All of them	4				
Severe storms	2				
Drought	1	4			
Low clouds	0	5			

a. For items mentioned more than once; 13 items mentioned only once not shown.

Overall, this information on individuals' exposure to, understanding of, and response to severe weather suggests that they may have significant values for improving severe weather forecasts, which is fundamentally different from that for day-to-day forecasts. This could be explored more thoroughly through similar survey instruments focused on specific types of severe weather where regional differences are important.

CHAPTER 5
VALUES FOR WEATHER FORECASTS

5.1 PRELIMINARIES TO VALUATION QUESTIONS

To introduce individuals to the concept of paying for improved weather forecasts and to create a realistic payment mechanism, Question 13 explains who pays for weather forecasting services and asked individuals their preferences for taxes to support NWS activities. Table 5-1 shows that while 62% of subjects say spending should remain about the same, fewer than 6% would like to see spending reduced and more than 32% would support increased taxes for improved weather forecasting services. This is a preliminary question that does not provide specific scenarios for forecast improvements and thus serves as a general indicator of respondents' attitudes about funding weather forecast improvements.

Table 5-1
Which of the Following Options Do You Prefer for Spending for the NWS for Weather Forecasting? (Q13)

Option	n	Percent
Do less and spend less on weather forecasting.	21	5.5%
Do and spend about the same on weather forecasting.	235	61.7%
Do more and spend more on weather forecasting.	125	32.8%

Economic theory indicates that an individuals' willingness to pay for a commodity is constrained by her income. Given the hypothetical nature of stated preference questions, some researchers have suggested that individuals may respond to such questions without considering their budget constraint. One approach suggested for remedying this in stated preference surveys is to remind individuals of their budget constraint (e.g., see the discussion of Fischhoff and Furby, 1988, in Section 2.3.1). Question 14 introduces the range of costs that individuals may incur for a weather forecast improvement program: "Programs to improve weather forecasts could cost households between \$3 and \$24 a year as long the improvements in weather forecasts were maintained."

Question 14 then reminds individuals of their budget by asking them where they would reduce their other spending if they were to increase their spending on weather forecasts or forecast improvements (If you had to pay \$24 a year in increased taxes, would you reduce spending in these categories to cover this additional expense?) and asks for a simple yes/no response to eight different expenditure categories. These categories are roughly based on the expenditure categories listed in the Statistical Abstract of the United States (http://www.census.gov/prod/2001pubs/statab/sec14.pdf last accessed January 18, 2002) of the Consumer Expenditure Survey.

Table 5-2 shows the percentage saying that they would reduce spending in a given expenditure category. The primary area where individuals indicated they would reduce expenditures is entertainment expenses, followed by clothing and services and savings or investments. Housing, health care, and food received less than 10% positive responses, consistent with their being "necessities."

Table 5-2
Responses to Budget Constraint Question

Expenditure Category	Percent Saying Would Reduce in This Category
Food (Q14a)	7.3
Housing (Q14b)	3.9
Clothing and services (Q14c)	25.5
Transportation (Q14d)	14.2
Health care (Q14e)	6.0
Entertainment (Q14f)	56.7
Savings or investments (Q14g)	23.9
Other expenditures (Q14h)	16.7

The only significant intercity difference in responses to the budget constraint was with respect to individuals' ability to reduce housing expenditures (Kruskal-Wallis test, $\chi^2 = 15.16$, $p = 0.06$). The percentage of respondents saying that they would reduce housing expenditures ranged from none in Billings, Denver, and Madison to 12.5% in Miami. This suggests that respondents from Miami perceive that they have more flexibility in their housing expenditures than do those in other cities.

5.2 ANALYSIS OF STATED CHOICE QUESTIONS

The utility an individual, *i*, gets from the use of weather forecasts is assumed to be:

$$U_i = \beta_Y (Y_i - Cost) + \beta_{Fr} Freq + \beta_{OD} OneDay + \beta_{MD} Multiday + \beta_{GD} GeogDetail \qquad (5\text{-}1)$$

where Y_i is individual *i*'s income, *Cost* is the cost of the weather forecast improvement program, *Freq* is the frequency of weather forecast updates, *OneDay* is the accuracy of one-day forecasts, *Multiday* is the accuracy of multiday forecasts, and *GeogDetail* is the number of miles measuring the geographic accuracy of weather forecasts. With this model there are no nonlinearities, meaning that the marginal value of an attribute is constant across all levels of that attribute. The parameter β_y represents the marginal utility of income, which is constant and expected to be positive.[1] The other parameters represent the marginal utilities for the weather forecast attributes. Because improvements in forecast quality are indicated by increases in the measures of *Freq*, *OneDay*, and *Multiday*, and decreases in the measure of *GeogDetail*, it is expected that the signs of the parameters are positive on *Freq*, *OneDay*, and *Multiday*, and negative on *GeogDetail*.

For current analysis, homogeneous preferences are assumed (all individuals have the same demand parameters). Two models are estimated based on the treatment of the followup question regarding the "do nothing" option. The first model is based on only the choice between Alternative A and Alternative B; this is called the A-B model. The second model, the A-B-Nothing model, includes the possibility that individuals would prefer no changes from current conditions and incorporates the responses from the followup question in a conditional probit model. An additional specification of the A-B-Nothing model is to estimate a separate variance of the error term for the status quo. This allows us to examine whether the response task is different for the followup question compared to the A-B choice questions. See Appendix F for a technical derivation of the econometric model.[2]

With 381 subjects each answering 9 choice questions, there are a total of 3429 choice question responses. Appendix E presents the choice frequencies by version for each of the choice questions and the followup questions. Table 5-3 presents the results of the models.

1. See Appendix F for statistical models exploring marginal utility of income as a function of sociodemographic characteristics.

2. The model was estimated using Maxlik in GAUSS.

Table 5-3
Conditional Probit Analysis

Parameters	A-B Model (common variance) Estimates	A-B Model (common variance) Std. Err.	A-B-Nothing Model (common variance) Estimates	A-B-Nothing Model (common variance) Std. Err.	A-B-Nothing Model (independent variances) Estimates	A-B-Nothing Model (independent variances) Std. Err.
Frequency of update (updates each day)	-0.045 ***	0.005	-0.014 **	0.007	-0.046 ***	0.005
Accuracy of one day forecasts (percent accurate)	0.061 ***	0.004	0.033 ***	0.004	0.062 ***	0.004
Accuracy of multiday forecasts (days into future forecast is useful)	0.032 ***	0.005	0.023 ***	0.006	0.032 ***	0.005
Geographic detail (miles)	-0.008 ***	0.002	-0.004 **	0.002	-0.008 ***	0.002
Household cost ($ per year per household)	-0.085 ***	0.006	-0.034 ***	0.003	-0.087 ***	0.005
Number of cases	3429		3429		3429	
Log-likelihood	-2180.24		-2294.55		-4474.36	

*, **, *** indicate significance at the 10%, 5%, and 1% level, respectively, using two-tailed tests of significance.

As seen in Table 5-3, for the A-B model all of the parameters are significant at the 1% level of significance. Frequency is statistically significant but of a different sign than expected in all models. The sign on frequency indicates that increasing the frequency of updates decreases utility. While this is similar to findings reported in Table 4-19, which suggested that forecast updates of 4 times a day are adequate for most purposes, the result is unexpected to the extent that if the frequency of updates were to increase, individuals could simply ignore the updates and be no worse off.[3]

In the A-B-Nothing common variance model, all of the parameters are significant at the 1% level except frequency and geographic detail, which are both significant at less than 2%. It should be noted that a negative sign on geographic detail is expected because decreasing the number of

3. If for some reason individuals felt that increased frequency of updates meant that they had to hear the updates every time they occurred, there could be an "annoyance" aspect of increasing updates.

miles covered by a forecast (increasing resolution) is expected to lead to increases (or at least not decrease) in utility. In the A-B-Nothing independent variance model, all of the parameters are significant at the 1% level.

The parameter estimates represent the marginal utility for a unit change in the attribute. The parameter estimate on cost thus represents the marginal utility of income. Dividing the marginal utility of an attribute level by the marginal utility of income yields an estimate of the monetary value of a unit change in the attribute. Table 5-4 shows these monetary values for the A-B-Nothing independent variance model.

Table 5-4
Marginal Monetary Value for Unit Change in Attributes
(A-B-Nothing Independent Variance Model)

Attribute	Parameter Estimate	Marginal Value
Frequency of updates (times a day)	-0.046	-$0.53
Accuracy of one-day forecasts (percent accurate)	0.062	$0.71
Accuracy of multiday forecasts (days into future forecast useful)	0.032	$0.37
Geographic detail (miles)	-0.008	-$0.09

Using the marginal utilities of the attributes and the marginal utility of income, it is possible to estimate the value for different combinations of attribute levels. For comparison with the values elicited in the SV question, we calculate the values for maximum improvements in all forecast attributes (Table 5-5) for the A-B-Nothing independent variance model.

This value is $12.25 per year per household using the A-B-Nothing independent variance model when the decrement in value from increased frequency is included. Given that resources should not be allocated to increase frequency should it prove undesirable to do so, we also calculate the benefit of increasing all attributes to their maximum levels without increasing frequency. In this case the A-B-Nothing independent variance model yields a benefit estimate of $16.48 per year per household.

Total utility changes for improving the accuracy of one-day forecasts constitute the largest positive portion of total value (about 65%). Improving the accuracy of multiday forecasts and improving geographic detail constitute 20% and 15% of total value, respectively.

Table 5-5
Calculations for Value of Maximum Improvements in All Forecast Attributes[a]

Parameters	Change from Baseline to Maximum	A-B-Nothing	
		Parameter Estimates	Attribute Utility Change
Cost		-0.087	
Frequency	8	-0.046	-0.368
One day	15	0.062	0.930
Multiday	9	0.032	0.288
Geographic detail	-27	-0.008	0.216
		Total utility change (with frequency)	1.066
		Total value (with frequency)	$12.25
		Total utility change (w/o frequency)	1.434
		Total value (w/o frequency)	$16.48

a. This table reports and uses parameter estimates to the third significant digit. We do not suggest that parameter estimates are accurate to this degree of significance.

Using a modified Krinsky-Robb method (Krinsky and Robb, 1986, 1990) (setting covariances between parameter estimates to zero), we simulated 95% confidence intervals for the value of improving all attributes to their maximum. Including the decrement to value from increasing frequency, the 95% confidence interval is $9.81 to $14.89. Without frequency the value to households of improving weather forecasts to the maximum feasible levels is between $13.91 and $19.54.

5.3 ANALYSIS OF STATED VALUE (WTP) QUESTIONS

WTP response to the stated value question (Question 33) requires certain adjustments before regression analysis. These adjustments include examining the responses to Question 34 for indications of scenario rejection and examining Questions 35 and 36 to deal with potential embedding.

5.3.1 Factor Analysis Scoring for Potential Scenario Rejection

Question 34 asked respondents to rate numerous statements with respect to how much such a concept affected their response to the valuation questions. Table 5-6 shows a factor analysis of this question. The "reason" column indicates our a priori expectation of the validity of each response in reaction to a valuation scenario. A "reject" in this column indicated that we expect that an individual who indicates that the reason affected his response to the valuation questions is potentially rejecting the scenario. A "valid" indicates that we consider these as valid positive or negative influences on WTP.

Table 5-6
Question 34: Rotated Factor Pattern

Q	Rotated Factor Pattern	Reason	Reject	Accept
Q34I	Money would not be used for program	Reject	**0.63**	-0.07
Q34B	Should not have to pay	Reject	**0.59**	-0.15
Q34E	Program will not work or will not happen	Reject	**0.51**	0.05
Q34J	Need more information	Reject	**0.50**	0.06
Q34G	Private sector should take over weather forecasting	Reject	**0.47**	0.05
Q34H	Do not use weather forecasts	Valid	**0.44**	-0.28
Q34D	Important to improve weather forecasting	Valid	0.04	**0.84**
Q34C	Useful to have improved weather forecasting	Valid	0.00	**0.81**
Q34K	Current weather forecasts are good enough	Valid	0.38	**-0.53**
Q34F	My responsibility to pay for improvement	Valid	0.08	**0.45**
Q34A	Cannot afford more	Valid	0.36	0.03

Bold indicates the loading of a scale on a factor (absolute value > 0.40).

The analysis generated two factors with eigenvalues greater than 1 (see Hatcher, 1994). The first factor, labeled "reject," includes most of the responses, which suggest rejection of some aspect of the valuation scenario, including the thoughts that the program wouldn't work or the money wouldn't go to the program. This factor also included one valid reason for stating a low WTP: "Do not use weather forecasts." The factor labeled "accept" includes the concepts likely to indicate that improved weather forecasts have a positive value to the individual.

Factor scores for these two factors were generated for each individual to be used in the Tobit regression as potential explanatory variables (see also Kinnell et al., 2002, for the use of factor scores in Tobit analysis). These are used in the analysis of the WTP responses along with the factor scores generated from the analysis of Question 4 on individuals' uses of weather forecasts in behavioral decisions. Summary statistics for these four factors are presented in Table 5-7.

Table 5-7
Summary Statistics on Individual Factor Scores

Factor	Mean	SD	Min	Max	n
Discretionary time use of forecasts	0	0.776	-2.095	1.409	381
Nondiscretionary time use of forecasts	0	0.743	-1.970	1.590	381
Rejection	0	0.855	-1.292	3.243	381
Acceptance	0	0.899	-1.784	1.772	381

Adjustments for Embedding

As discussed previously, embedding, or joint valuation, occurs when individuals state values for a more inclusive commodity than that being "offered" by the researcher. For weather forecasts this may occur if individuals feel that improving day-to-day weather forecasts will also lead to improvements in other weather forecasts, such as those for severe weather, or the forecast improvements would also benefit others (see Section 2.3.1 on embedding). In this case, the respondent may interpret the hypothetical commodity as being more or less inclusive than the investigator intends. Understanding the respondents' knowledge base will aid in discerning whether or not joint valuations are likely to occur and how they can be minimized. We included Questions 35 and 36 in the survey instrument to help discern peoples' perceptions of the valued good (see Schulze et al., 1998). The more explicit the scenario, all else equal, the less likely the occurrence of embedding effects, particularly if the scenario description addresses sources of confusion identified in the pretest. Nonetheless, embedding may be a problem for valuing certain goods because of the way that people form their preferences for them.

Individuals were asked about potential motivations related to their stated WTP. If their responses indicated potential embedding, individuals were then asked to indicate what percentage of their stated WTP is "for improvements in weather forecasting under *normal* weather conditions." This percentage is used to adjust stated WTP to a value statement for just normal weather condition forecast improvements. Unadjusted and adjusted WTP values are reported in Table 5-8. Ninety-eight individuals (29.5%) answered Question 35 indicating that their value was just for normal weather. Nearly 13% of respondents did not answer Question 35, suggesting that some individuals were confused by the skip pattern designed for this question. For the 234 individuals

Table 5-8
Unadjusted and Adjusted WTP Values

WTP	Mean	SD	Median	Min	Max	n
Unadjusted	$12.72	13.84	8.00	0	100	381
Adjusted for embedding	$7.47	9.55	4.20	0	56	381

who indicated some form of embedding, the average percentage of their stated value that they allocated just to normal weather was 45.8% (standard deviation of 30.8). Overall, WTP values were reduced 41% through the "disembedding" adjustment.

It should be noted that the WTP values averaged in Table 5-8 are stated WTP for the different improvement programs described in the 20 different versions of the survey and thus this is not a mean WTP for any particular program.

5.3.2 Tobit Regression

Tobit models were used to analyze the stated value data because the willingness-to-pay bids were left-censored at zero (15% of the unadjusted bids are zero). Tobit regressions account for the truncation at zero of the WTP bids, improving the model's ability to produce unbiased estimates (Kmenta, 1986).

Table 5-9 shows four regressions using different dependent variables and different weighting variables. The two dependent variables are the unadjusted (raw) WTP values and the embedding-adjusted WTP values. Each regression was run unweighted and then weighted using the simple sum of the individuals' responses to Questions 38 and 39 as a weight. Question 38 asked, "How confident do you feel about the choices you made" in the valuation questions, and Question 39 asked, "How much do you think that your answers . . . represent what you would like the NWS to do to improve weather forecasting technology?" These questions are used as a self-evaluation of respondents' comprehension of the valuation tasks and thus we explore using them to self-adjust the reliability of the responses to the WTP questions.

Sociodemographic variables are modeled to explore how WTP varies between individuals. It is usually expected that higher income people are willing to pay more (and able to) for most normal economic goods. Income is positive and significant only in the regressions weighted by "represent." There are no a priori expectations on the sign of any of the other sociodemographic variables except that higher education is often correlated with income and thus associated with a higher WTP.

Table 5-9
Tobit Regression of WTP (n = 381)
(std error in parenthesis)

Dependent Variable	WTP (raw)		WTP Embedding Adjusted	
Noncensored values	323		310	
Left-censored values	58		71	
Weighting variable	None	Represent	None	Represent
Parameter	Estimate	Estimate	Estimate	Estimate
Intercept	-0.688 (7.025)	-2.601 (2.622)	-9.158 (29.543)	-8.302 (10.980)
Age (years)	0.133 (0.051) ***	0.152 (0.019) ***	0.029 (0.216)	0.097 (0.083)
Income ($1,000s)	0.021 (0.023)	0.026 (0.009) ***	0.0661 (0.101)	0.072 (0.038) *
Education (years)	-0.442 (0.371)	-0.493 (0.138) ***	0.109 (1.635)	-0.811 (0.613)
Gender (male = -1; female = +1)	-0.281 (0.758)	-0.390 (0.284)	3.589 (3.298)	3.953 (1.246) ***
Ethnicity (white = 1, all others = 0)	-0.148 (1.893)	0.059 (0.707)	2.066 (7.901)	0.376 (2.955)
Work outside (percent of time)	-0.009 (0.029)	-0.006 (0.011)	-0.311 (0.126) **	-0.381 (0.049) ***
Leisure outside (percent of time)	0.035 (0.038)	0.036 (0.014) **	0.011 (0.162)	0.028 (0.060)
Discretionary time use of forecasts factor	2.099 (1.076) *	2.087 (0.340) ***	-1.926 (4.837)	-1.448 (1.793)
Nondiscretionary time use of forecasts factor	-2.207 (1.182) *	-1.873 (0.438) ***	-4.266 (5.339)	-4.908 (1.990) **
Weather variability (mean one day max temp difference)	1.277 (0.785)	1.640 (0.296) ***	8.731 (3.502) **	11.666 (1.368) ***
Frequency	0.023 (0.242)	-0.022 (0.092)	0.879 (1.072)	1.054 (0.409) ***
One day	0.417 (0.139) ***	0.437 (0.052) ***	1.716 (0.647) ***	1.882 (0.245) ***
Multiday	-0.013 (0.228)	-0.013 (0.085)	-0.213 (0.979)	-0.103 (0.365)
Geographic	-0.133 (0.075) *	-0.137 (0.028) ***	-0.413 (0.319)	-0.414 (0.120) ***

Table 5-9
Tobit Regression of WTP (n = 381)
(std error in parenthesis) (cont.)

Dependent Variable	**WTP (raw)**		**WTP Embedding Adjusted**	
Rejection	-3.755 (0.859) ***	-3.639 (0.325) ***	-14.076 (3.730) ***	-14.766 (1.415) ***
Acceptance	7.900 (0.881) ***	8.169 (0.326) ***	33.665 (5.796) ***	36.430 (2.239) ***
Scale	13.383 (0.535	13.707 (0.200)	37.641 (5.453)	37.644 (2.014)
Log likelihood	-1339.489	-10111.3	-162.502	-1156.901
***, **, * significant at the 1%, 5%, and 10% levels respectively.				

It is expected that the amount of time spent outside, whether on the job or for recreation, may relate to individuals' WTP for improved forecasts. "Work outside" is significant only in the adjusted WTP equation weighted by "represent," and "leisure outside" is significant in both weighted regressions. In both cases, the more time an individual spends outdoors the more valuable improved weather forecasting is to him.

The more that an individual indicated she used weather forecasts for making discretionary decisions, measured by the "discretionary time use of forecasts factor," the more value she indicated she would receive from improved weather forecasts.

Weather variability in an individual's location, measured as the mean of 24-hour maximum temperature differential, is significant in the weighted regression, suggesting that individuals experiencing greater weather variability are willing to pay more for improved weather forecasts.

The attributes of the weather improvement program offered are also expected to affect stated WTP values. Consistent with findings reported earlier regarding individuals' ratings of the usefulness of increased forecast frequency, frequency is significant in only one of the models. The improvement in accuracy of one-day forecasts is highly significant and of the expected sign in all the regressions. Improved geographic accuracy is significant and of the expected sign in three of the four models. Unexpectedly, improvements in multiday accuracy is not significant in any of the models.

Finally, as an approach to control for potential scenario rejection, we included the factor scores from Question 34 as explanatory variables in the WTP model. As expected, individuals with a higher "reject" score stated a significantly lower WTP for improved weather forecasts. If these individuals reject some aspect of the scenario, such as having to pay a tax or perhaps not being sure that such a program was feasible, they will understate their true value for weather forecast improvements. Similarly, individuals with a high "accept" score responded to Question 34 suggesting that improved weather forecasts were important to them for a variety of reasons. The accept factor is more likely an endogenous indicator of the importance of improved weather forecasts to the individual and thus likely to be highly correlated with WTP.

In general the WTP responses are consistent with economic theory and expectations about values for improvements in a normal good, weather forecasts. Individuals are willing to pay more for a higher quality commodity (e.g., better one-day forecasts and better geographic detail), they are willing to pay more for it the more they use it in their decision making (as indicated by the discretionary use factor), and they are willing to pay more the more likely it is to affect their decision making (e.g., the more unpredictable the weather is where they live and the more time they spend outside on the job or leisure).

Using the mean sample values for the sociodemographic characteristics of the sample (age, income, education, gender, ethnicity, work outside, leisure outside) and the average weather variability, we used the Tobit regression estimates to approximate the value of improving all forecast attributes to their maximum level. For the unadjusted WTP, these estimates are $12.35 from the unweighted regression and $12.21 from the weighted regression (this includes frequency). We compare these value estimate for improving all attributes to their maximum level to the corresponding value estimate from the stated choice analysis of $12.25 to indicate that these approaches are yielding similar value estimates for forecast improvements.

5.4 VALUE OF CURRENT WEATHER SERVICES

Following the main valuation portion of the survey, several questions explored issues related to the value of current weather services and respondent perceptions regarding forecasting and severe weather. As shown in Chapter 3 and repeated here, Question O1 and O2 explored individuals' values for current weather forecast services. Figure 5-1 shows Question O1, which asked individuals how important to them current weather forecast services are for all types of weather related activities.

For the 379 individuals who answered this question, the mean response of 4.16 (SD = 0.93) suggests that overall weather forecasts are moderately to very important for individuals when one also considers their use during severe weather conditions or for specialized uses such as aviation or marine commerce. Overall there was no significant difference in the distribution of answers to Question O1 by city (Kruskal-Wallis test 3.28, df = 8, Pr > chi-square 0.92).

Question 02 in the followup questions elicits limited information on individuals' values for current weather services. According to Hooke and Pielke (2000), current total federal spending on weather forecasting services is $2,596 million, for an average of $24.79/year per household. Spending within the Department of Commerce for all meteorological operations and supporting research is $1,374 million, for an average of $13.12/year per household (Hooke and Pielke, 2000; Table 5-1). The 2002 fiscal year budget for the NWS (and NESDIS) was $1,383 million or

Figure 5-1
Importance of Current Weather Forecast Services (Question O1)

O1 In the first part of this survey we discussed only the normal weather observations and forecasts provided by the NWS. In addition to these normal weather observations and forecasts, the NWS and the federal government also provide forecast information on:

- Severe weather forecasts including watches and warnings
- Forecasts used for aviation and marine commerce
- Information provided to private weather services.

Thinking now about all of the forecast information services provided by the NWS listed above, how important to you are weather forecasts for all types of weather related activities?

(CIRCLE THE NUMBER OF YOUR ANSWER.)

Not at all important	A little important	Somewhat important	Moderately important	VERY IMPORTANT
1	2	3	4	5

about $13.20 per household (see Table 5-10). Based on this range, in the Denver pilot study we indicated three different current costs ($5, $10, and $20) to households and asked individuals if they felt this amount was worth it to them. Based on the pilot study responses, where 80% of individuals said “yes” to $20 a year, we extended the range of indicated costs to $96 a year. The final survey indicated costs of $2, $5, $10, $32, $64, and $96 a year per household as indicated in Table 5-11.

Figure 5-2 shows the valuation question (Question O2) for an indicated value of $10 per year per household.

Table 5-12 shows the number of subjects that received and responded to each cost level indicated in Question O2. The third column indicates the number that said that the current value of all weather forecast services was equal to or greater than the cost indicated. The fourth column (% Yes) shows the percentage that responded either “Currently worth $X a year to my household” or “Currently worth more than $X a year to my household” by cost level. As can be seen, the percent yes decreases as the cost increases (as would be expected from economic theory for a normal good); 60.6% still said that the value of all current weather forecast services was equal to or greater than $96 per year.

Table 5-10
Derivation of Per Household Expenditures for Federal Funding of Weather Forecast Services (Fiscal Year 2002, millions$[a])

National Environmental Satellite, Data and Information Service (NESDIS)	Operations, Research and Facilities (ORF)[b]	$77.9
	Procurement, Acquisition and Construction (PAC)	$561.9
National Weather Service (NWS)	Operations, Research and Facilities (ORF)	$672.3
	Procurement, Acquisition and Construction (PAC)	$70.7
	Total	$1,382.8
	Per household[c]	$13.21

a. Based on information in an email from Donna Rivelli, of the Budget Formulation and Program Analysis Division of the NWS, to Rodney Weiher forwarded to Jeff Lazo 7/18/2002 12:23 PM.
b. Excludes $64 million from NESDIS ORF that is slated for data centers.
c. 104,705,000 households as of March 2000.
Source: U.S. Census, 2000. 2002 per household costs are presumably marginally lower due to population increase from 2000 to 2002.

Table 5-11
Dollars Costs Indicated for Question O2

Survey Version	Annual Household Cost Indicated
5, 9, 13, 15	$2
4, 6, 14, 17	$5
1, 3, 8, 10	$10
7, 11, 12, 18	$32
16, 19	$64
2, 20	$96

Given current costs of about $13.20 a year for NWS services, there appear to be significant aggregate benefits generated by current weather service activities. With 81% of respondents indicating $32 or more per year willingness to pay for current services and current average household costs of $13.20/year, this suggests that 81% of the population has net benefits exceeding $18.80 per household per year for current services. Given the format of the question, this value encompasses all NWS forecast information, including that for normal weather, severe weather, aviation, and marine forecasts and not just day-to-day forecast information.

Figure 5-2
Value of Current Weather Forecast Services Valuation (Question O2)

O2 All of the activities of the NWS are paid for through taxes as a part of the federal government. This money pays for all of the observation equipment (such as satellites and radar), analysis, and reporting activities of the NWS. As discussed above, in addition to normal weather observations and forecasts, the NWS provides services such as severe weather forecasts, including watches and warnings, forecasts used for aviation and marine commerce, and information provided to private weather services.

Suppose that you were told that about $10 a year of your household's taxes went to paying for all of the weather forecasting services of the NWS and the federal government. Do you feel that the services you receive from the activities of the NWS are worth more than, less than, or exactly $10 a year to your household? *(CIRCLE THE NUMBER OF YOUR ANSWER.)*

1 Currently worth less than $10 a year to my household

2 Currently worth $10 a year to my household

3 Currently worth more than $10 a year to my household

Table 5-12
Response to Question O2

Current Annual Cost	Number Answering Version with This Cost Indicated	Number Yes	% Yes
$2	80	73	91.3%
$5	71	63	88.7%
$10	81	70	86.4%
$32	74	60	81.1%
$64	40	26	65.0%
$96	33	20	60.6%

We emphasize that this question is not a WTP question such as the stated value question asked with respect to improved forecast services. This question asks individuals if the current weather forecast services are worth the current costs. The fact that 81% of the individuals stated that current services are worth at least $32 a year indicates that 81% of the individuals would have a WTP for these services of *at least* $32 and possibly much more. The approach provides relevant and reliable information on the value of current weather services that are not included in the other valuation questions in the survey (which deal with improvements to weather forecasts). To our knowledge there is no recent or reliable estimate of the monetary value of current weather services to households.

Table 5-13 examines the relationship between individuals' responses to the current forecast importance and valuation questions (O1 and O2, respectively) and the cost indicated in their survey. There is no significant correlation between current cost and importance of "weather forecasts for all types of weather related activities." This may suggest that individuals' answers to Question O1 were not significantly influenced by the dollar amount indicated for the cost of forecasts in this section. In the terminology of nonmarket valuation, this would mean that there was little or no anchoring on the indicated costs — anchoring is considered a potential bias in nonmarket valuation questions.

Table 5-13
Correlations between Questions for Value of Current Weather Forecasts
Pearson Correlation Coefficient: Prob > |r| under H0: Rho = 0 (n = 378)

	Cost	**Importance (O1)**	**Valuation (O2)**
Cost	1.000		
Importance (O1)	0.011 (0.825)	1.000	
Valuation (O2)	-0.392 (<.001)	0.265 (<.001)	1.000

There is a positive and significant correlation between importance of forecasts (O1) and value of current forecasts (O2). As would be expected, the more important a commodity is to an individual the more valuable that commodity is to him monetarily. Finally, there is a negative and significant correlation between cost of current forecasts and response as to whether or not it is currently worth that amount (O2). This again would be expected if different individuals have different values for weather forecasts and, in general, if forecasts are a normal good where demand will decrease as price or cost increases.

To further model and explore the value information provided by Question O2 we conducted linear regression analysis using two approaches. The first approach models the "percent yes" as a function of cost using the percent yes by group as the independent variable (e.g., Column "% Yes" from Table 5-12). The second models the responses to Question O2 individually. Both models set "currently worth $X a year to my household" and "currently worth more than $X a year to my household" responses to Question O2 equal to 1 and responses of "currently worth less than $X a year to my household" equal to 0.

Table 5-14 shows results for the model when only the percent accepting current cost by category is used — thus there are only six observations (one for each dollar cost level indicated). The coefficient on cost is negative and significant, indicating that as the cost indicated increases the percent saying that it is worth it to them decreases, as would be expected.

Table 5-14
Regression on Group Percent Yes Responses

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.9057	0.0157	61.49	<0.01
Current cost	-0.0034	0.0003	-11.21	<0.01
Adjusted R^2 = 0.96; n = 6.				

Using the regression information from Table 5-14, we calculate the cost that would be required to generate a 50% acceptance rate. This indicates the expected median value of the sample — the value where half of the people would say it is worth it to them and half would say that it is not worth it to them.

Calculation of the median value involves solving $\%Yes = \alpha + \beta \text{Cost}$ for the implied cost of when *%Yes* is set equal to 50%. The median value based on parameter estimates from the regression reported in Table 5-14 is $119 per year per household. As an approach to generating aggregate values, the median is equivalent to using the principle of majority voting (Hanemann and Kanninen, 1996, p. 20).

It should also be noted that based on analysis of the intercept term for the regression reported in Table 5-14, we reject the null hypothesis that the intercept is equal to 1. This means that the intercept is less than 100%, suggesting that (using a linear function) even if the cost were zero some individuals (about 10%) would say that they are unwilling to pay for current weather forecast services. In general it is reasonable to assume that if a commodity costs nothing then individuals will at least say that it is worth at least that much to them as they can always simply ignore the commodity and not consume it. One possible explanation for the projected 10%

"no's" at zero cost is that some individuals react negatively to the concept of a tax and, regardless of whether that tax is zero, they are still opposed to provision of that commodity through taxation. If this is the case then the expected median value of $119 is an underestimate of the true median value.

Table 5-15 shows the linear regression using individual responses to Question O2 as the dependent variable coded as before (1 = worth at least the cost indicated, 0 = not worth the cost indicated). Calculating a median value based on this regression yields an estimate of $109 per year per household. It should be noted that these two regressions and median value estimates are two approaches using the same data where the first regression simply uses grouped data. Based on this approach we expect the median household willingness to pay for the current level of weather forecast services to be in the $100-$120 range for this sample of the population. Again, given that the intercept is significantly less than 1, the calculated median is most likely an understatement of the true median value (given a linear model).

Table 5-15
Regression on Individual Yes Responses

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.9111	0.0254	35.87	<0.01
Current cost	-0.0038	0.0007	-5.67	<0.01
Adjusted R^2 = 0.076; n = 380.				

Finally, because the response variable has been coded into a binary yes-no response, we explore individuals' answers to Question O2 as a function of cost and their sociodemographic characteristics using a probit model. Table 5-16 shows the results of the probit model with Question O2 coded as before (1 = worth at least the cost indicated, 0 = not worth the cost indicated).

As costs to the household increase, fewer respondents say that their value for current weather forecasts is equal to or greater than the cost. This is consistent with a downward sloping demand curve generally posited by economic theory. As income increases, more individuals will say the commodity is worth the cost, although this variable is not significant at the 10% level. Education is significant, indicating that more highly educated respondents place a higher value on current weather forecast information (without education in the model income is significant, indicating a degree of correlation between income and education). Gender and household size are not significant in explaining the value of current weather forecasts to the household.

Table 5-16
Probit Analysis of Current Value Responses (O2) (n = 378)

Parameter	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	-1.363	0.766	3.17	0.085
Current cost (2001$ per hh per yr)	-0.014	0.003	28.45	<.01
Age (years)	0.013	0.006	4.45	0.04
Income (1,000s $2001)	0.038	0.029	1.77	0.18
Gender (-1 = male; +1 = female)	0.104	0.088	1.41	0.24
Education (years)	0.100	0.046	4.75	0.03
Household size	-0.035	0.055	0.42	0.52
Weather variability	0.099	0.050	3.96	0.05
Discretionary use factor	0.215	0.123	3.06	0.08
Nondiscretionary use factor	-0.152	0.132	1.33	0.25
Hours spent travelling to work (H6)	0.011	0.007	2.81	0.09
Hours spent outside around house (H8)	-0.003	0.008	0.16	0.69

Weather variability for an individual's city is significantly and positively related to the value of current forecasts. This means that increased weather variability in an individual's city (measured as the mean of the absolute value of the one-day change in maximum temperature over the period 1994 to 2000; see Table 3-6) leads to an increased value for current weather forecast information. This result indicates that respondents who live in areas with greater day-to-day weather variability (e.g., Denver or Billings) place a higher value on the current weather forecast system than those living in areas with less weather variability (e.g., San Diego), all else equal.

The coefficient estimate on the discretionary use factor derived from Question 4 (see Table 5-7) is positive and significant. This indicates that respondents who stated that they use weather forecasts more for discretionary decisions (planning social activities, vacations, or weekend activities) place a higher value on weather forecasts. The coefficient estimate on the nondiscretionary use factor was not significant, indicating that current weather forecasts do not add significant value for behavioral decisions over which individuals have less control (e.g., what to wear to work or what to do at work or school that day).

Individuals who spend more of their time “traveling outside to and from work or school in a mode that could be affected by the weather” (Question H6) also place a higher value on the current weather forecast system. Hours spent “working outside in your yard or garden, washing your car, working on the house, or other activities ‘around the house’” (Question H8) was not significant in explaining individuals’ response to whether or not the current cost of weather forecasts was worth it to them. Questions H6 and H8 provided more explanatory power in this model than the previously used measures of the percentage of time the individual spent working or recreating outdoors based on Questions H5 and H7.

As reported in Table 5-14, we conducted simple linear regression analysis of the percentage answering yes to the different dollar levels. Using the regression, we calculated fitted values for each dollar level. The observed and fitted “% Yes” are shown in the second and third columns of Table 5-17, respectively (the “Observed % Yes is repeated here from Table 5-11). The last two columns show the lower and upper 95% confidence intervals for the population proportions based on the survey sample. These confidence intervals are calculated using Eq. 5-1 for the confidence intervals for population proportions from sample data (Mansfield, 1991, p. 282):

$$p \pm z_{\alpha/2}\sqrt{\frac{p(1-p)}{n}}\ , \tag{5-1}$$

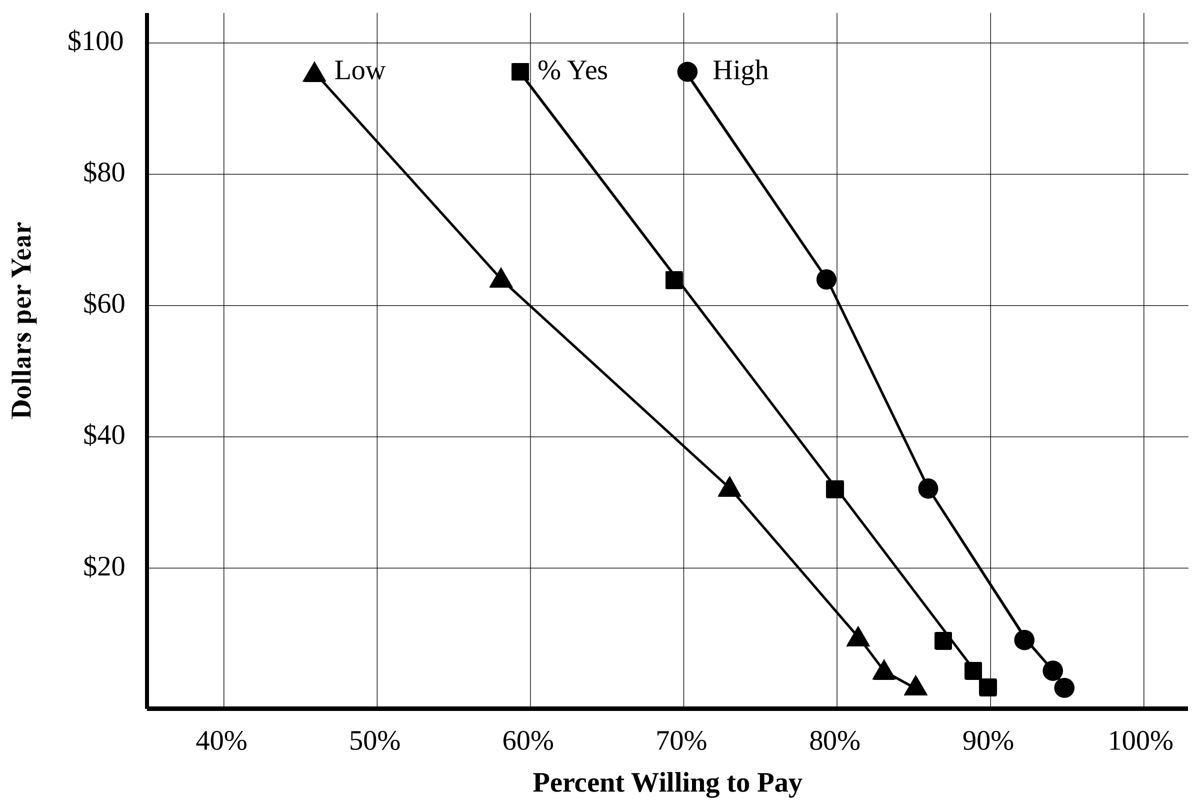
where p is the sample proportion, $z_{\alpha/2}$ is the value of the standard normal variable that is exceeded with probability $\alpha/2$ (in this case α = 5%), and n is the sample size.

Table 5-17
Response to Question O2

Current Annual Cost	Observed % Yes	Fitted % Yes	95% Confidence Interval	
			Low	High
$2	91.3%	89.89%	85.2%	94.6%
$5	88.7%	88.88%	83.7%	94.1%
$10	86.4%	87.20%	82.0%	92.4%
$32	81.1%	79.80%	73.3%	86.3%
$64	65.0%	69.04%	58.8%	79.3%
$96	60.6%	58.28%	46.3%	70.3%

Based on the regression analysis, the line labeled % Yes in Figure 5-3 shows the fitted values for the percentage of individuals willing to pay at least X dollars ($2, $5, $10, $32, $64, or $96) a year for current services. This traces out a demand curve for current services in the range of values offered in Question O2. Figure 5-3 also plots 95% confidence intervals for the lower and upper bounds for the population proportion. The wider confidence intervals at $64 and $96 are primarily a function of the smaller sample for these two versions of the survey.[4] Since we had anticipated a much lower acceptance rate at these dollar levels based on the Denver pilot test, we included these cost levels in only two versions each, and included $2, $5, $10, and $32 in four versions each.

Figure 5-3
Household Demand for Current Weather Services



4. The derivative of Eq. 5-1 with respect to n is negative, indicating that as the sample size decreases the width of the confidence interval increases, all else equal.

Given per household costs for current weather forecast services of about $25 per year (if one considers all federal spending on weather forecast services), there is a significant net benefit to the nation from the public provision of weather forecast services.

CHAPTER 6
SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

"Information is power" is a common adage. Weather forecasts provide individuals with information — this empowers them to make better decisions. Forecasts, to the extent that they provide information useful to individuals, make people better off, and thus forecasts have value. Better forecasts, to the extent that they provide even better information to individuals, make people even better off, and thus better forecasts have even more value.

6.1 KEY FINDINGS

- The median household value for current weather forecasts for all weather conditions is about $109 a year. With about 105 million U.S. households, taking the median value as an estimate of the average household value, aggregate national values for all current weather forecast services are $11.4 billion a year. With total federal spending on weather forecasting services about $25 a year per household (Hooke and Pielke, 2000), this study suggests a benefit-cost ratio of 4.4 to 1. A simple benefit-cost calculation indicates a net national benefit of $8.82 billion a year. This may be an underestimate of aggregate benefits because (1) median values are often less than mean values in stated preference surveys; (2) this estimate may not include values generated outside of the household sector, such as in agriculture, transportation, or construction; and (3) this does not include potential benefits to households in other countries that rely on meteorological data from the United States.

- The average household would be willing to pay about $16 a year to have forecast quality improved to the maximum technically feasible level. The aggregate national benefit for improving day-to-day forecasts to the maximum feasible level is $1.73 billion a year.

- These results are robust across locations. There is a strong value signal across all of our cities, with differences across locations reflecting geographic differences in weather variability. Values are robust across individuals and differences across individuals reflect reasonable differences in the use of weather forecast information.

- The results are consistent with the literature and common sense. Similar to prior studies, it was found that individuals consider precipitation and temperature the most important attributes of weather forecasts. It was found that individuals do use weather forecasts in making behavioral decisions, at least for decisions for which there may be some degree of flexibility, such as weekend recreational activities. Consistent with the responses to the following valuation questions, individuals indicated that improvements in the accuracy of one-day forecasts were most important and increasing the frequency of forecast updates was least important. Consistent with expectations, differences in how individuals perceive or and use weather forecast information are related to gender, education, income, age, employment activities, and leisure activities.

6.2 A THOUGHT EXERCISE

The National Weather Service undertook the Modernization and Associated Restructuring (MAR) program in the 1980s to upgrade observing systems such as satellites and radars, and to design and develop advanced forecaster computer workstations. These collectively cost about $4.5 billion over about 20 years.

Since we have no estimate of the costs required to improve weather forecasts to their maximum feasible level as evaluated for the current study, let’s assume it would cost twice what the MAR program cost and would take 20 years to complete. Let’s further assume that there would be increased maintenance and operation costs beginning in the tenth year of $60 million a year, or almost a 5% increase in the NWS’s current operating budget. Finally, let’s assume that limited benefits are seen beginning in the tenth year and these increase linearly over 10 years to the full level of benefits estimated in this study, $1.73 billion a year.

Using a 5% rate of discount the net present value of such a program (calculated over a 100 year time horizon) is $9.9 billion. This means that the present value of the benefits of this program are about 2.5 times as much as the present value of all of the costs, both capital costs and maintenance and operation over the relevant time period, even though the maximum benefits are assumed to be delayed until the twentieth year of the program. Overall these assumptions imply a 9.7% internal rate of return for the weather forecast improvement program.

This thought experiment shows how the values estimated from a study such as this could be used in policy decision making to evaluate the benefits and costs of weather forecast improvement programs. It would be important in considering any specific program as extensive as this to undertake more program-specific benefit evaluation. The methods used in this study are highly amenable to such future tasks as well as evaluation of other weather forecast improvement options.

6.3 VALIDITY AND RELIABILITY OF THE STUDY RESULTS

We obtained responses from 381 individuals for our survey. Sampling experts suggest a sample size of about 1,200 subjects to obtain parameter estimates within 3% of population values. Ceteris paribus, a smaller sample still provides unbiased estimates of the population values — the confidence intervals are simply a little larger.

Our sample comprised individuals from nine sites across the country. Two aspects of the randomness of our sample are (1) central site implementation and (2) implementation at nine sites. While not totally random, the approach of randomly recruiting individuals to self-administer the survey at a central location may actually improve the quality of data — a benefit to weigh against the quantity of data obtained by other methods. Central site implementation of the survey provides for payment of a significant incentive in a researcher controlled setting. This control of the implementation setting helps keep individuals on task, allows for in-person instruction on survey administration, and allows for reduced item nonresponse through the review of surveys for completed answers. The nine sites were chosen so that there is one in each of the nine regions used by NCDC for climate data analysis. We consider the nine sites to be representative of the variability of weather and climate country-wide as well as the variability of the sociodemographic characteristics of respondents.

We believe that we have thus captured the essence of individuals' values for current and improved weather forecasts. While a much larger sample may allow for more precise parameter estimates, we believe that the results of this study provide unbiased, reliable, and valid value estimates.

6.4 RELIABILITY OF STATED PREFERENCES

Do survey respondents to this survey believe the values elicited in the survey represent their preferences? We asked, **"**How much do you think that your answers . . . represent what you would like the NWS to do to improve weather forecasting technology?" The average response of 3.6 (where 1 = "Do not represent my desires at all" and 5 = "Represent my desires completely") indicates that individuals do feel that policy makers should pay attention to and use their responses because they represent their preferences for weather forecast programs. There was not a significant difference in responses to this question between the nine different cities.

Weather forecasts are used by most individuals virtually every day, suggesting that forecast information is well understood — people clearly understand how they use weather information and can readily identify how good, or bad, information affects them. Under these conditions, stated preference data are expected to be least susceptible to errors that may lead to biased value estimates. However, protest responses (especially tied to higher taxes) are sometimes hard to overcome and may reduce stated values. Early parts of the survey, those sections before the choice questions, allowed individuals to obtain or consider information about the commodity (weather forecasts) and at the same time provided data on their attitudes about the commodity (e.g., their perceptions and uses of weather forecasts). Individuals' responses to these sections (see Chapter 4) revealed a high degree of consistent and reasonable responses — especially considered in light of individuals' situations (e.g., weather variability where they live, how much work time they spend outside). This consistency between attitudes, perceptions, uses, and values lends support to considering the value estimates as valid and reliable.

6.5 FUTURE WORK

6.5.1 Extending the Current Work

The current survey instrument can serve as a basis for additional research to extend our knowledge about households' values for current and improved weather forecasts. The survey could be implemented at more regional sites chosen to complement the weather variability or sociodemographic characteristics of the current sample. Increasing the sample size beyond that used in the current survey could allow for more precise parameter estimation and could also allow for more in-depth examination of differences between and within specific subgroups (e.g., between those who do and don't spend more than 50% of their job time or leisure time outside).

Alternative implementation methods should be considered, including mail surveys or implementation through the internet (e.g., WebTV). Mail survey implementation would allow for a more geographically diverse sample to be reached. Implementation through the internet could allow for a higher degree of control of the implementation process by including different versions of questions based on responses to earlier questions. Such approaches would provide a richer data set to provide a better understanding of households' perceptions of, uses of, and values for current and improved weather forecasts.

6.5.2 Other Service Packages

Several questions regarding current and improved severe weather forecasts were asked in the survey. Responses suggest that many individuals feel that improvements in forecasts for severe weather would be beneficial. Further research is indicated on the value of improvements in severe weather forecasting as well as other weather forecast services such as river stage forecasts and seasonal to interannual forecasts. These include:

- improve severe weather forecasts and warnings
- improve river stage forecasts
- improve forecasts for large-scale weather systems
- improve seasonal to interannual forecasts.

There has been relatively little work on valuation of these types of weather forecast information using methods discussed in this report. While some studies have used market approaches to value the impacts of various weather *events* (e.g., the damages from a hurricane or a tornado), there has been little work to understand households' perceptions of, use of, and values for weather and climate forecast information. Stratus Consulting is currently in the initial phases of a study of the value of improved hurricane forecast information.

6.5.3 Revealed Preference Information

Given the quasi-public goods nature of weather forecasts, stated preference methods are the preferred approach for eliciting values for weather forecasts, especially for improvements in weather forecasts with which individuals do not have current experience. While the current study focused on the assessment of stated preference methods for eliciting values for improved and current weather information, the feasibility of obtaining revealed preference information should be further explored. Such information could supplement the stated preference data and may serve well in specific case studies of the uses and impacts of both correct and incorrect forecast information.

Casual observation suggests that significant resources are devoted by television, radio, and newspaper to provide weather forecasts to the general public. It seems likely that decisions by media groups providing this information are based on extensive marketing analysis of consumer demands for these services. While much of this information is most likely proprietary, it may be possible to confidentially obtain and analyze this information. This could be undertaken initially as a case study. Revealed preference data would provide support for values obtained using stated preference methods. Revealed preference valuation could provide important information on values for current weather forecast services, but may be of less help in valuing improvements in weather forecast information.

CHAPTER 7
REFERENCES

Abramowitz, M. and I. Stegun. 1964. Handbook of Mathematical Functions, with Formulas, Graphs and Math Tables. National Bureau of Standards, Applied Math Series 55. U.S. Government Printing Office, Washington, DC.

Adamowicz, W., J. Louviere, and M. Williams. 1994. "Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities." *Journal of Environmental Economics and Management* 26:271-292.

Adamowicz, W.L., J. Louviere, and J. Swait. 1998. Introduction to Attribute-Based Stated Choice Methods. Final Report. Resource Valuation Branch, Damage Assessment Center, National Oceanic and Atmospheric Administration. Prepared by Advanis.

Adamowicz, W., P. Boxall, M. Williams, and J. Louviere. 1996. Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments versus Contingent Valuation. Working Paper.

Adamowicz, W., P. Boxall, M. Williams, and J. Louviere. 1998. "Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments and Contingent Valuation." *American Journal of Agricultural Economics* 80:64-75.

Adamowicz, W.L., J. Swait, P. Boxall, J. Louviere, and M. Williams. 1997. "Perceptions versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Models of Environmental Valuation." *Journal of Environmental Economics and Management* 32:65-84.

Agarwal, M.K. and P.E. Green. 1991. "Adaptive Conjoint Analysis versus Self-Explicated Models: Some Empirical Results." *International Journal of Marketing* 8:141-146.

Amemiya, T. 1994. *Introduction to Statistics and Econometrics.* Harvard University Press, Cambridge, MA.

Anaman, K.A. and S.C. Lellyett. 1996. "Contingent Valuation Study of the Public Weather Service in the Sydney Metropolitan Area." *Economic Papers* 15(3):64-77.

Anaman, K.A., D.J. Thampapillai, A. Henderson-Sellers, P.F. Noar, and P.J. Sullivan. 1995. "Methods for Assessing the Benefits of Meteorological Services in Australia." *Meteorological Applications* 2:17-19.

Anaman, K.A., S.C. Lellyett, L. Drake, R.J. Leigh, A. Henderson-Sellers, P.F. Noar, P.J. Sullivan, and D.J. Thampapillai. 1997. Economics and Social Benefits of Meteorological Services Provided by the Australian Bureau of Meteorology: Final Project Report. MacQuarie University, Bureau of Meteorology, Sydney.

Anaman, K.A., S.C. Lellyett, L. Drake, R.J. Leigh, A. Henderson-Sellers, P.F. Noar, P.J. Sullivan, and D.J. Thampapillai. 1998. "Benefits of Meteorological Services: Evidence from Recent Research in Australia." *Meteorological Applications* 5(2):103-115.

Anderson, J.E. 1979. "On the Measurement of Welfare Costs under Uncertainty." *Southern Economic Journal* 45:1160-1171.

ASA. 2000. A Discussion of Selected Weather, Water and Climate Forecasts and Services: Pilot Study of the Value of Improved Weather Forecasts. Atmospheric Science Advisors, LLC, Silver Spring, MD.

Batsell, R.R. and J.J. Louviere. 1991. "Experimental Analysis of Choice." *Marketing Letters* 2:199-214.

Beggs, S., S. Cardell, and J. Hausman. 1981. "Assessing the Potential Demand for Electric Cars." *Journal of Econometrics* 16:1-19.

Ben-Akiva, M. and S. Lerman. 1994. *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press, Cambridge, MA.

Bishop, R.C., W.S. Breffle, J.K. Lazo, R.D. Rowe, and S.M. Wytinck. 2000. Restoration Scaling Based on Total Value Equivalency: Green Bay Natural Resource Damage Assessment. Report prepared for U.S. Fish and Wildlife Service, U.S. Department of Interior, and U.S. Department of Justice.

Bjornstad, D.J. and J.R. Kahn (eds.). 1996. *The Contingent Valuation of Environmental Resources: Methodological Issues and Research Needs*. Elgar, Cheltenham, U.K.

Bradley, M. and A. Daly. 1994. "Use of the Logit Scaling Approach to Test for Rank Order and Fatigue Effects in Stated Preference Data." *Transportation* 21:167-184.

Breffle, W.S. and R.D. Rowe. Forthcoming. "Comparing Choice Question Formats for Evaluating Natural Resource Tradeoffs." *Land Economics* 78(2).

Breffle, W.S., E.R. Morey, R.D. Rowe, D.M. Waldman, and S.M. Wytinck. 1999. Recreational Fishing Damages from Fish Consumption Advisories in the Waters of Green Bay. Prepared for the U.S. Fish and Wildlife Service by Stratus Consulting Inc., Boulder, CO. November 1.

Butler, J. and R. Moffit. 1982. "A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model." *Econometrica* 50:761-764.

Carson, R.T., N.E. Flores, K.M. Martin, and J.L. Wright. 1996. “Contingent Valuation and Revealed Preference Methodologies: Comparing the Estimates for Quasi-Public Goods.” *Land Economics* 72(1):80-99.

Cattin, P. and D.R. Wittink. 1982. “Commercial Use of Conjoint Analysis: A Survey.” *Journal of Marketing* 46:44-53.

Cavlovic, A., J. Forkes, and K. Rollins. No date — a. Economic Value of Environment Canada’s ATAD Service for Business Users in the Greater Toronto Area. Unpublished Report.

Cavlovic, A., J. Forkes, and K. Rollins. No date — b. Economic Value of Environment Canada’s Weatheradio Service for Users in Maritime Communities of Atlantic Canada. Unpublished Report. Submitted to The Policy Program and International Affairs Directorate, Atmospheric Environment Service, Environment Canada.

Chapman, R.E. 1992. Benefit-Cost Analysis for the Modernization and Associated Restructuring of the National Weather Service. NISTIR 4867. Report to the U.S. Department of Commerce, National Institute of Standards and Technology.

Choi, E.K. and S.R. Johnson. 1987. “Consumer’s Surplus and Price Uncertainty.” *International Economic Review* 28:407-411.

Colman, B. 1997. “What Is a Good Weather Forecast? in the Eyes of a Forecaster.” Presented at the Workshop on the Social and Economic Impacts of Weather, April 2-4, Boulder, CO.

Cornes, R. and T. Sandler. 1996. *The Theory of Externalities, Public Goods and Club Goods*. 2nd edition. Cambridge University Press, New York.

Cummings, R.G., D.S. Brookshire, and W. Schulze. 1986. *Valuing Environmental Goods: An Assessment of the Contingent Valuation Method*. Rowan and Allanheld, Totowa, NJ.

Curtis, J.C. and A.H. Murphy. 1985. “Public Interpretation and Understanding of Forecast Terminology: Some Results of a Newspaper Survey in Seattle, Washington.” *Bulletin of the American Meteorological Society* 66:810-819.

Davis, D.R. and S. Nnaji. 1982. “The Information Needed to Evaluate the Worth of Uncertain Information, Predictions and Forecasts.” *Journal of Applied Meteorology* 21:461-470.

Ehrendorfer, M. and A.H. Murphy. 1992. “On the Relationship between the Quality and Value of Weather and Climate Forecasting Systems.” *Idöjárás* 96:187-206.

Elrod, T., J.J. Louviere, and K.S. Davey. 1992. “An Empirical Comparison of Ratings-Based and Choice-Based Conjoint Models.” *Journal of Marketing Research* 30:368-377.

Ericsson, K.A. and H.A. Simon. 1993. *Protocol Analysis: Verbal Reports as Data*. Bradford Book, MIT Press, Cambridge, MA.

Fischhoff, B. and L. Furby. 1988. “Measuring Values: A Conceptual Framework for Interpreting Transactions with Special Reference to Contingent Valuation of Visibility.” *Journal of Risk and Uncertainty* 1:147-184.

Freebairn, J.W. and J.W. Zillman. No date — a. Economic Benefits of Meteorological Services. Unpublished Paper. Department of Economics, The University of Melbourne, Parkville, VIC, Australia.

Freebairn, J.W. and J.W. Zillman. No date — b. Funding Meteorological Services. Unpublished Paper. Department of Economics, The University of Melbourne, Parkville, VIC, Australia.

Freeman, A.M. 1993. The Measurement of Environmental and Resource Values: Theory and Methods. Resources for the Future, Washington, DC.

Gan, C. and E.J. Luzar. 1993. “A Conjoint Analysis of Waterfowl Hunting in Louisiana.” *Journal of Agricultural and Applied Economics* 25(2):36-45.

Gould, J.P. 1974. “Risk, Stochastic Preference, and the Value of Information.” *Journal of Economic Theory* 8:64-84.

Green, P.E. and V. Srinivasan. 1990. “Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice.” *Journal of Marketing* October:3-19.

Hanemann, W.M. 1991. “Willingness to Pay and Willingness to Accept: How Much Can They Differ.” *American Economic Review* 81:635-647.

Hanemann, W.M. and B. Kanninen. 1996. The Statistical Analysis of Discrete-Response CV Data. June 1996. Working Paper 798. California Agricultural Experiment Station, Giannini Foundation of Agricultural Economics. University of California at Berkeley.

Hatcher, L.D. 1994. A Step-by-Step Approach to Using the SAS System for Factor Analysis and Structural Equation Modeling. SAS Institute, Inc., Cary, NC.

Hausman, J. and D. Wise. 1978. “A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences.” *Econometrica* 45:403-426.

Hensher, D.A. 1994. “Stated Preference Analysis of Travel Choices: The State of Practice.” *Transportation* 21:107-133.

Hess, J. 1982. “Risk and the Gain from Information.” *Journal of Economic Theory* 27:231-238.

Hildreth, C. and C. Houck. 1968. "Some Estimators for a Linear Model with Random Coefficients." *Journal of the American Statistical Association* 63:584-595.

Hilton, R.W. 1981. "The Determinants of Information Value: Synthesizing Some General Results." *Management Science* 27:57-64.

Hooke, W.H. and R.A. Pielke, Jr. 2000. "Short Term Weather Prediction: An Orchestra in Need of a Conductor." In *Prediction: Decision-Making and the Future of Nature*, D. Sarewitz, R.A. Pielke, Jr., and R. Byerly, Jr. (eds.). Island Press, Washington, DC. pp. 61-84.

Hsiao, C. 1975. "Some Estimation Methods for a Random Coefficient Model." *Econometrica* 43:305-325.

Huber, J. and K. Zwerina. 1996. "The Importance of Utility Balance in Efficient Choice Designs." *Journal of Marketing Research* 33(August):307-317.

Johnson, F.R. and W.H. Desvousges. 1997. "Estimating Stated Preferences with Rated-Pair Data: Environmental, Health, and Employment Effects of Energy Programs." *Journal of Environmental Economics and Management* 34:79-99.

Johnson, S.R. and M.T. Holt. 1997. "The Value of Weather Information." Chapter 3 in *Economic Value of Weather and Climate Forecasts*, R.W. Katz and A.H. Murphy (eds.). Cambridge University Press, Cambridge, U.K.

Johnson, F.R., W.H. Desvousges, E.E. Fries, and L.L. Wood. 1995. Conjoint Analysis of Individual and Aggregate Environmental Preferences. Triangle Economic Research Technical Working Paper No. T-9502.

Just, R.E., D.L. Hueth, and A. Schmitz. 1982. *Applied Welfare Economics and Public Policy*. Prentice-Hall, Englewood Cliffs, NJ.

Kinnell, J., J.K. Lazo, D.J. Epp, A. Fisher, and J. Shortle. 2002. "Perceptions and Values for Preventing Ecosystem Change: Pennsylvania Duck Hunters and the Prairie Pothole Region." *Land Economics* 78(2):228-244.

Kmenta, J. 1986. *Elements of Econometrics*. 2nd edition. Macmillan Publishing Company, New York.

Kopp, R., W. Pommerehne, and N. Schwarz, eds. 1997. *Determining the Value of Non-Market Goods: Economic, Psychological, and Policy Relevant Aspects of Contingent Valuation Methods*. Kluwer, Boston.

Krinsky, I. and A.L. Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *Review of Economics and Statistics* 68:715-719.

Krinsky, I. and A.L. Robb. 1990. "On Approximating the Statistical Properties of Elasticities: A Correction." *The Review of Economics and Statistics* 77:189-190.

Kuhfeld, W.F. 1996. "Multinomial Logit, Discrete Choice Modeling: An Introduction to Designing Choice Experiments, Collecting, Processing, and Analyzing Choice Data with the SAS© System." SAS Institute Inc., Cary, NC.

Layton, D. and G. Brown. 1998. Heterogeneous Preferences regarding Global Climate Change. Presented at NOAA Applications of Stated Preference Methods to Resource Compensation Workshop, Washington, DC.

Leipper, D.F. 1994. "Fog on the U.S. West Coast: A Review." *Bulletin of the American Meteorological Society* 75:229-240.

Louviere, J.J. 1988. "Conjoint Analysis Modeling of Stated Preferences." *Journal of Transport Economics and Policy* 10:93-119.

Louviere, J.J. 1992. "Experimental Choice Analysis: Introduction and Overview." *Journal of Business Research* 24:89-95.

Louviere, J.J. 1994. "Conjoint Analysis." In *Advances in Marketing Research*, R. Bagozzi (ed.). Blackwell Publishers, Cambridge, MA.

Louviere, J.J. and G. Woodward. 1983. "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregated Data." *Journal of Marketing Research* 20:350-367.

Louviere, J.J., D.A. Hensher, and J.D. Swait. 2001. *Stated Choice Methods: Analysis and Application*. Cambridge University Press, Cambridge, U.K.

Macauley, M.K. 1997. Some Dimensions of the Value of Weather Information: General Principles and a Taxonomy of Empirical Approaches. Presented at the Workshop on the Social and Economic Impacts of Weather 2-4 April 1997, Boulder, CO. www.dir.ucar.edu/erig/SOCASP/weather1/macauley/html. Accessed September 1999.

Magat, W.A., W.K. Viscusi, and J. Huber. 1988. "Paired Comparison and Contingent Valuation Approaches to Morbidity Risk Valuation." *Journal of Environmental Economics and Management* 15:395-411.

Mansfield, E. 1991. *Statistics for Business and Economics.* 4th edition. W.W. Norton and Co., New York.

Mathews, K.E., W.H. Desvousges, F.R. Johnson, and M.C. Ruby. 1997. Using Economic Models to Inform Restoration Decisions: The Lavaca Bay, Texas Experience. Paper presented at the Conference on Restoration of Lost Human Uses of the Environment, Washington, DC. May.

Mazzotta, M.J. and J.J. Opaluch. 1995. “Decisionmaking When Choices Are Complex: A Test of Heiner’s Hypothesis.” *Land Economics* 71(4):500-515.

McClelland, G.H., W.D. Schulze, J.K. Lazo, D.M. Waldman, J.K. Doyle, S.R. Elliot, and J.R. Irwin. 1993. Methods for Measuring Non-Use Values: A Contingent Valuation Study of Groundwater Cleanup. Draft Final Report to U.S. EPA. September.

Mitchell, R.C. and R.T. Carson. 1989. *Using Surveys to Value Public Goods: The Contingent Valuation Method*. Resources for the Future, Washington, DC.

Mjelde, J.W., S.T. Sonka, and D.S. Peel. 1989. The Socioeconomic Value of Climate and Weather Forecasting: A Review. Research Report 89-01. Midwestern Climate Center, Illinois State Water Survey, Champaign.

Morey, E.R., T. Buchanan, and D.M. Waldman. 1999. Happy (hypothetical) Trails to You: The Impact of Trail Characteristics and Access Fees on a Mountain Biker’s Trail Selection and Consumer’s Surplus. Working Paper, University of Colorado, Boulder.

Morey, E.R., K.G. Rossmann, L. Chestnut, and S. Ragland. In press. Estimating E[WTP] for Reducing Acid Deposition Injuries to Cultural Resources: Using Choice Experiments in a Group Setting to Estimate Passive-Use Values. Chapter 10 in *Valuing Cultural Heritage: Applying Environmental Valuation Techniques to Historic Buildings, Monuments and Artifacts,* S. Narvud and R.C. Ready (eds.). Edward Elgar Publishing Ltd, Brookfield, VT.

MSI Services Incorporated. 1981. Public Requirements for Weather Information and Attitudes Concerning Weather Service. Prepared for the National Weather Service.

Murphy, A.H. 1993. “What is a Good Forecast? An Essay on the Nature of Goodness in Weather Forecasting.” *Weather and Forecasting* 8:281-293.

Murphy, A.H. 1994. Socio-Economic Value of Climate Forecasts. Report to Economics Group, Office of the Chief Scientist, National Oceanic and Atmospheric Administration.

Murphy, A.H. 1997. “Forecast Verification.” Chapter 2 in *Economic Value of Weather and Climate Forecasts,* R.W. Katz and A.H. Murphy (eds.). Cambridge University Press, Cambridge, U.K. pp. 19-74.

Murphy, A.H. and B.G. Brown. 1983. “Forecast Terminology: Composition and Interpretation of Public Weather Forecasts.” *Bulletin of the American Meteorological Society* 64:13-22.

Murphy, A.H., S. Lichtenstein, B. Fischhoff, and R.L. Winkler. 1980. “Misinterpretations of Precipitation Probability Forecasts.” *Bulletin of the American Meteorological Society* 61:695-701.

Opaluch, J.J., S.K. Swallow, T. Weaver, C.W. Wessells, and D. Wichelns. 1993. "Evaluating Impacts from Noxious Facilities: Including Public Preferences in Current Siting Mechanisms." *Journal of Environmental Economics and Management* 24:41-59.

Phlips, L. 1988. *The Economics of Imperfect Information*. Cambridge University Press, New York.

Pielke, R.A. and R.A. Peilke. 1997. *Hurricanes: Their Nature and Impacts on Society*. John Wiley & Sons, New York.

Pope, C.A. 1992. Viewer Perceptions of Severe Weather and Broadcast Meteorologists, Vol. II. Masters thesis, Mississippi State University, Starkville.

Prototype Regional Observing and Forecasting Service. 1979. Report of a Study to Estimate Economic and Convenience Benefits of Improved Local Weather Forecasts. NOAA Technical Memorandum ERL PROFS-1. NOAA Environmental Research Laboratory, Boulder, CO.

Roe, B., K.J. Boyle, and M.F. Teisl. 1996. "Using Conjoint Analysis to Derive Estimates of Compensating Variation." *Journal of Environmental Economics and Management* 31:145-150.

Rosenfeld, J. 2000a. "Do We Need the National Weather Service?" *Scientific American Presents: Weather, 2000* 11(1):28-31.

Rosenfeld, J. 2000b. "The Butterfly that Roared." *Scientific American Presents: Weather, 2000.* 11(1):22-27.

Rothschild, M. and J.E. Stiglitz. 1970. "Increasing Risk II: A Definition." *Journal of Economic Theory* 2(3):225-243.

Rothschild, M. and J.E. Stiglitz. 1971. "Increasing Risk II: Its Economic Consequences." *Journal of Economic Theory* 3(1):66-84.

Rowe, R.D., W.D. Schulze, and W.S. Breffle. 1996. "A Test for Payment Card Biases." *Journal of Environmental Economics and Management* 31:178-185.

Schulze, W.D., G.H. McClelland, J.K. Lazo, and R.D. Rowe. 1998. "Embedding and Calibration in Measuring Non-Use Values." *Journal of Resource and Energy Economics* 20:163-178.

Smith, J.C. 1995. Testimony before the Senate Government Affairs Committee on the Elimination of the Department of Commerce. Commercial Weather Services Association.

Stewart, T.R. 1997. Forecast Value: Descriptive Decision Studies. Chapter 5 in *Economic Value of Weather and Climate Forecasts*, R.W. Katz and A.H. Murphy (eds.). Cambridge University Press, Cambridge, U.K.

Suchman, D., B. Auvine, and B. Hinton. 1981. “Determining Economic Benefits of Satellite Data in Short-Range Forecasting.” *Bulletin of the American Meteorological Society* 62(10):1458-1465.

Swait, J. and W. Adamowicz. 1996. The Effect of Choice Environment and Task Demand on Consumer Behavior: Discriminating between Contribution and Confusion. Rural Economy Staff Paper 96-09. University of Alberta, Department of Rural Economy, Edmonton, Canada.

Swait, J. and W. Adamowicz. 2000. Choice Environment, Market Complexity and Consumer Behavior: A Theoretical and Empirical Approach for Incorporating Decision Complexity into Models of Consumer Choice. Working Paper. University of Florida.

Swamy, P. 1970. “Efficient Inference in a Random Coefficient Regression Model.” *Econometrica* 38:311-323.

Train, K. 1998. “Recreational Demand Models with Taste Differences Over People.” *Land Economics* 74:230-239.

U.S. Census. 2000. Current Population Survey, Table 1. http://www.census.gov/prod/2001pubs/p20-537.pdf. Accessed March 27, 2002.

Viscusi, W.K., W.A. Magat, and J. Huber. 1991. “Pricing Environmental Health Risks: Survey Assessments of Risk-Risk and Risk-Dollar Trade-Offs for Chronic Bronchitis.” *Journal of Environmental Economics and Management* 21:32-51.

Waldman, D. 1985. “Computation in Duration Models with Heterogeneity.” *Journal of Econometrics* 28:127-134.

Wilks, D.S. 1997. “Forecast Value: Prescriptive Decision Studies.” Chapter 4 in *Economic Value of Weather and Climate Forecasts*, R.W. Katz and A.H. Murphy (eds.). Cambridge University Press, Cambridge, U.K.

Wittink, D.R. and P. Cattin. 1989. “Commercial Use of Conjoint Analysis: An Update.” *Journal of Marketing* 53:91-96.

APPENDIX A
TELEPHONE SCREENER

PUBLIC POLICY STUDY SCREENER

INTRO. My name is **[__caller's name__]** and I am calling from Discovery Research Group, a professional international research firm. We are interested in learning more about what people in your area think about some public policy issues. This research study is not related in any way to the recent national tragedy, but about other public policy issues. On [DATE], we are holding sessions with people to get a better understanding of people's opinions. To thank people for taking the time to share their opinions, we will be giving participants $40 when the session is done.

Before I tell you more about the session, I'd like to ask you a few questions about yourself and your household.

IF NEEDED: At these sessions, we will hand out a survey that contains questions about a number of public policy issues. There are no right or wrong answers to these questions and we are not trying to sell anything; In order to get a variety of opinions, we want to talk with people from a wide variety of backgrounds and experiences.

IF NEEDED: I would like to stress that this is not a marketing or sales call. Answering these questions should only take about 5 minutes. All answers will be kept confidential.

B1. Are you 18 years of age or older?

1 18 or more years of age ---------> Continue to B4

2 Less than 18 years

B2. Is there [someone/male/female] in your household I may speak to who is 18 years of age or older?

1 No -----------------------------> *TERMINATE*

2 Yes -----------------------------> Have that person put on the phone (SKIP TO INTRO)

B4. What is your age?

______ years ------------→ if refused, go to B4a

B4a. Which of the following categories best describes your age?

1. 18 to 25 years
2. 26 to 45 years
3. 46 to 65 years
4. 66 to 75 years
5. Over 75 years
9. REFUSED

B5. Which of the following categories best describes your race?

1. White
2. Black or African-American
3. Asian or Pacific Islander
4. American Indian or Alaska Native
5. Other → Specify:
9. REFUSED

B6. Are you of Spanish, Hispanic or Latino descent?

1. Yes
2. No
9. REFUSED

B7. Which of the following best describes the highest level of education you have completed?

1. Did not complete high school
2. High school diploma or equivalent
3. Some college, two year college degree or technical school
4. Four year college graduate
5. Master’s degree
6. Professional degree or doctorate
9. REFUSED

B8. What was your total household income for 2000 before taxes?

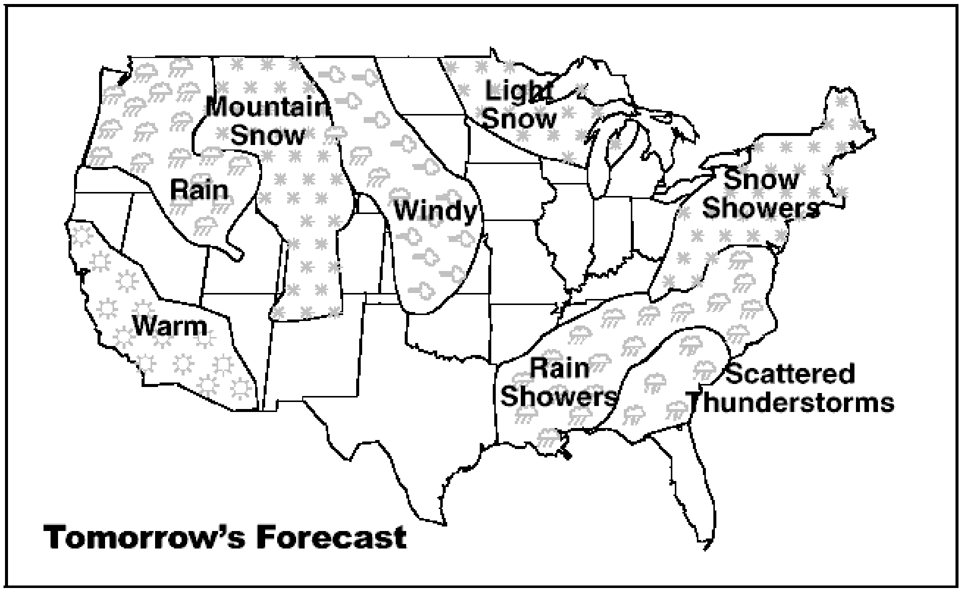
1. Under $10,000
2. $10,000 to $19,999
3. $20,000 to $29,999
4. $30,000 to $39,999
5. $40,000 to $49,999
6. $50,000 to $59,999
7. $60,000 to $69,999
8. $70,000 to $79,999
9. $80,000 to $100,000
10. Above $100,000
99. REFUSED

B9. RECORD RESPONDENT’S GENDER

1. Male
2. Female

APPENDIX B
SURVEY INSTRUMENT

IMPROVING WEATHER FORECASTS: HOW IMPORTANT IS IT TO YOU?



IMPORTANT INFORMATION ABOUT THIS BOOKLET

In this booklet we are interested in weather forecasts during normal weather conditions, which include fair weather and stormy weather that is not rapidly changing or life threatening.

While potentially severe weather events such as tornadoes, floods, and extreme temperatures are important, please remember that in this booklet we are talking mainly about normal weather conditions.

You do not need any special knowledge about weather or weather forecasts to be able to answer the questions in this booklet.

1 **The National Weather Service (NWS) is the primary source of weather data, forecasts, and warnings for the United States. This federal agency runs the satellites, radars, supercomputers, and other equipment for gathering and analyzing weather data. Television, radio, and newspaper forecasts are all prepared using information from the NWS.**

Have you heard of the NWS before today? *Circle the number of your answer.*

1. Yes
2. No

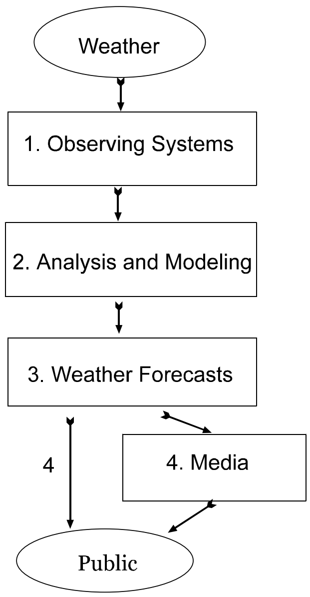
2 **A typical weather forecast provides information about the chance and amount of rain or snow, how cloudy it will be, the low and high temperatures, how windy it will be, and the air pressure (barometric pressure).**

How important to you are the different types of information in a weather forecast? *Circle the number of your answer for each item.*

	Not at all important	A little important	Somewhat important	Moderately important	Extremely important
Chance of rain, snow, or hail	1	2	3	4	5
Amount of rain, snow, or hail	1	2	3	4	5
How cloudy it will be . . .	1	2	3	4	5
Low temperature	1	2	3	4	5
High temperature	1	2	3	4	5
How windy it will be	1	2	3	4	5
Air pressure	1	2	3	4	5

THE DIAGRAM SHOWS HOW WEATHER INFORMATION IS COLLECTED AND DELIVERED.

As can be seen in the diagram, satellites and equipment supplied by the federal government collect most of the data for weather forecasting, whether from the NWS or through the media.



1. Satellites, weather balloons, ground stations, and other equipment collect data from around the world. These data are shared by weather services throughout the world.

2. These data are then put into computers and analyzed to predict what the weather will be in the near future.

3. The NWS issues weather forecasts (as well as watches or warnings if needed).

4. Weather forecasts are provided to the public by the NWS, the media (including TV, radio, and press), and private weather services.

3 **How often do you obtain weather forecasts from each of the following sources?**
Circle the number of your answer for each item.

	Rarely or never	Once or more a month	Once or more a week	Daily	Twice a day	Three or more times a day
Local TV newscasts	1	2	3	4	5	6
Cable TV stations	1	2	3	4	5	6
Newspaper	1	2	3	4	5	6
Commercial or public radio .	1	2	3	4	5	6
NOAA Weather Radio	1	2	3	4	5	6
Internet	1	2	3	4	5	6
Other people	1	2	3	4	5	6

4 **How often do you use weather forecasts in planning for each of the activities listed below? Please remember that we are asking about how you use the weather forecast for *planning* activities (not on how you may change plans based on what the weather actually is at the time you do these activities).** *Circle the number of your answer for each item.*

	Never	Rarely	Half the time	Often	Most of the time
Dressing yourself or your children for the day	1	2	3	4	5
How to get to work, school, or the store	1	2	3	4	5
Job or business	1	2	3	4	5
House or yardwork	1	2	3	4	5
Social activities	1	2	3	4	5
Vacation or travel	1	2	3	4	5
Planning for the weekend . . .	1	2	3	4	5

Improving Weather Forecasting Technology

With no change in planned NWS budgets, forecast technologies and forecast quality will be the same in the future as they are now. The NWS could improve forecasts with several available technologies such as additional weather satellites, more advanced radars, improved computers and data analysis, and additional ground stations.

With more investment, weather forecasts could be improved by:

- **More frequently updated forecasts**
- **More accurate one-day forecasts**
- **More accurate multiday forecasts**
- **More geographic detail**

Each of these are discussed in turn on the following pages.

Please continue on the next page ☞

FREQUENCY OF UPDATED FORECASTS

5 **When the NWS updates a forecast, they gather new data from the satellites, radar, and other sources. NWS runs the weather forecast computer programs to provide new forecasts for each area. The NWS currently updates forecasts 4 times each day in normal weather conditions.**

Under normal weather conditions, how adequate do you think that 4 updates a day is?
Circle the number of your answer.

	Much less than adequate	Less than adequate	About right	More than adequate	Much more than adequate	Don't know
4 times a day is . .	1	2	3	4	5	9

6 **With new satellites, radar, computers, and improved computer programs, the NWS could increase the frequency of weather forecasts updates to as many as 12 times a day.**

Compared to the current 4 times a day, how useful would it be to you to have weather forecasts updated 6, 9, or 12 times a day under normal weather conditions?
Circle the number of your answer for each item.

	Not at all useful	A little useful	Somewhat useful	Very useful	Extremely useful
6 times a day	1	2	3	4	5
9 times a day	1	2	3	4	5
12 times a day	1	2	3	4	5

ACCURACY OF ONE-DAY FORECASTS

7 **One-day forecasts are forecasts for temperature, rain, snow or hail, wind, and other conditions up to 24 hours in advance. Current one-day forecasts for temperature and rain and snow are correct about 80% of the time (about 48 days out of every 60 days). "Correct" means that the predicted high and low temperatures are within 5 degrees of the actual temperatures and that they were right about whether or not there would be measurable rain or snow.**

Under normal weather conditions, how adequate do you think that 80% correct is? *Circle the number of your answer.*

	Much less than adequate	Less than adequate	About right	More than adequate	Much more than adequate	Don't know
Correct 80% of the time is.	1	2	3	4	5	9

8 **With improved technology, the NWS could increase the accuracy of one-day weather forecasts to as much as 95% correct. The following table shows the current and improved accuracy of one-day forecasts and how many days the weather forecast would be correct or incorrect out of 60 days (two months).**

Percent correct	Correct out of 60 days	Incorrect out of 60 days
Currently is correct 80% of the time	**48 days**	**12 days**
Improve to correct 85% of the time	**51 days**	**9 days**
Improve to correct 90% of the time	**54 days**	**6 days**
Improve to correct 95% of the time	**57 days**	**3 days**

Compared to the current 80% accuracy, how useful would it be to you to have one-day weather forecasts improved to be correct 85%, 90%, or 95% of the time? *Circle the number of your answer for each item.*

	Not at all useful	A little useful	Somewhat useful	Very useful	Extremely useful
Correct 85% of the time	1	2	3	4	5
Correct 90% of the time	1	2	3	4	5
Correct 95% of the time	1	2	3	4	5

ACCURACY OF MULTIDAY FORECASTS

9 **Multiday forecasts are forecasts for the temperature, rain and snow, cloud cover, and other conditions for several days in advance. A multiday forecast for an area is considered accurate if it provides better information about future weather than simply reporting the average weather conditions in the past for the same time of the year. Current multiday forecasts are accurate to 5 days in advance.**

Under normal weather conditions how adequate do you think that multiday forecasts accurate to 5 days in advance is? *Circle the number of your answer.*

	Much less than adequate	Less than adequate	About right	More than adequate	Much more than adequate	Don't know
Accurate to 5 days in advance is	1	2	3	4	5	9

10 **With improved technology, the NWS could increase the accuracy of multiday forecasts so that a 14-day forecast could be as accurate as 5-day forecasts are now.**

Compared to the current 5-day accuracy, how useful would it be to you to have multiday weather forecasts improved to be accurate to 7 days, 10 days, or 14 days? *Circle the number of your answer for each item.*

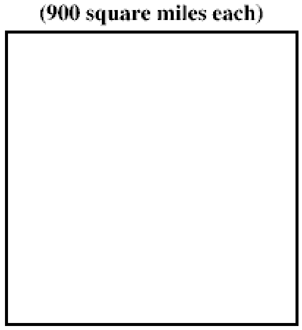
	Not at all useful	A little useful	Somewhat useful	Very useful	Extremely useful
7-day forecast as accurate as current 5-day forecast	1	2	3	4	5
10-day forecast as accurate as current 5-day forecast	1	2	3	4	5
14-day forecast as accurate as current 5-day forecast	1	2	3	4	5

GEOGRAPHIC DETAIL

11 **Geographic detail is how much area each forecast covers. Each weather forecast currently covers an area of about 30 miles by 30 miles (900 square miles). This means that NWS forecasts do not distinguish between different locations within this area (although sometimes local forecasters add more detail).**

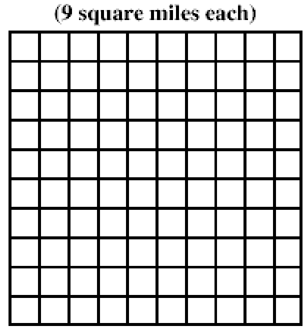
For comparison, the figure on the left below shows the area that is currently covered by a single forecast: every part of that area receives the same forecast. The figure on the right shows that with improvements to 3 miles by 3 miles: each smaller area receives a forecast specific to that location's conditions.

Geographic detail to 30 miles by 30 miles (900 square miles each)



One general forecast is issued for this area.

Geographic detail to 3 miles by 3 miles (9 square miles each)



Specific forecasts are issued for each of these areas.

Under normal weather conditions, how adequate do you think that geographic detail to 30 miles by 30 miles is? *Circle the number of your answer.*

	Much less than adequate	Less than adequate	About right	More than adequate	Much more than adequate	Don't know
Geographic detail to 30 miles by 30 miles	1	2	3	4	5	9

12 **With improved technology, the NWS could increase geographic detail of weather forecasts to 3 miles by 3 miles for an area of 9 square miles. Currently, forecasts are specific for an area of about 900 square miles.**

Compared to the current geographic detail of 30 miles by 30 miles (900 square miles), how useful would it be to you to have NWS weather forecasts that were detailed to 15 miles by 15 miles (225 square miles), 7 miles by 7 miles (49 square miles), or 3 miles by 3 miles (9 square miles)? *Circle the number of your answer for each item.*

	Not at all useful	A little useful	Somewhat useful	Very useful	Extremely useful
Detail to 15 miles by 15 miles (4 times more geographic detail than current)	1	2	3	4	5
Detail to 7 miles by 7 miles (18 times more geographic detail than current)	1	2	3	4	5
Detail to 3 miles by 3 miles (100 times more geographic detail than current)	1	2	3	4	5

Paying for Improved Weather Forecasts

13 **Increased spending to improve weather forecasts would pay for new satellites, radar, and computers, and for ongoing expenses for maintenance and personnel. Taxpayers will pay for any weather forecast improvements through federal taxes. Any additional costs to your household would be in addition to what you are now paying in taxes to support the NWS and would continue as long the improvements in weather forecasts were maintained.**

Which of the following options do you prefer for spending for the NWS for weather forecasting? *Circle the number of your answer.*

1 Do less and spend less on weather forecasting.

2 Do and spend about the same on weather forecasting.

3 Do more and spend more on weather forecasting.

14 **Programs to improve weather forecasts could cost households between $3 and $24 a year as long the improvements in weather forecasts were maintained. If you had to pay $24 a year in increased taxes, would you reduce spending in these categories to cover this additional expense?** *Circle either Yes or No for each spending category.*

Yes	No	**Food**
Yes	No	**Housing**
Yes	No	**Clothing and Services**
Yes	No	**Transportation**
Yes	No	**Health Care**
Yes	No	**Entertainment**
Yes	No	**Savings or Investments**
Yes	No	**Other Expenditures (*please describe* ___________________)**

What Program Do You Prefer?

On each of the following pages, please choose between one of the two programs, labeled Program A and Program B, that involve possible improvements in weather forecast updates, accuracy, and geographic detail (see Question 15 on the facing page).

- **Each column describes a program made up of a combination of possible weather forecast improvements provided by increasing weather forecasting resources. Please compare Program A with Program B and indicate which you prefer by putting a check mark (✔) in the box at the bottom of that column.**

- **Since we do not yet know how much each program will actually cost you or others, we present you with a range of costs.**

- **For each question, even if you do not view either Program A or B as ideal, still tell us which program you would prefer.**

- **After you make your choice between Program A and B, please tell us (at the bottom of the page) whether you prefer to have the program you just chose (A or B) or whether you would rather have no improvements and no added yearly cost.**

- **Without investments in a weather forecast improvement program, current forecasting conditions would be maintained in the future using current budget levels (no additional costs to the household). Remember that current weather forecasting conditions are:**

Frequency of updates	4 times a day
Accuracy of one-day forecasts	80% correct
Accuracy of multiday forecasts	Accurate to 5 days into the future
Geographic detail	Detail within 30 miles

- **For the first question only, we have added an extra column on the right hand side indicating the differences between Program A and Program B.**

15 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼	Difference between A and B
FREQUENCY OF UPDATED FORECASTS (Currently 4 times a day)	4 times a day (current)	12 times a day (8 times a day more than current)	Program B provides more frequent forecasts
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 80% of the time (current)	correct 80% of the time (current)	No change
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 5 days in the future (current)	accurate up to 5 days in the future (current)	No change
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 3 by 3 miles (100 times more detailed than current)	to 30 by 30 miles (current)	Program A is 100 times more detailed than current
ADDED YEARLY COST TO YOUR HOUSEHOLD	$3 more	$3 more	Both are $3 a year
Check (✔) the box for the program you prefer ➔	❑	❑	

16 **Would you rather the NWS continue with the current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.

2. Make the improvements in the program that I chose above and pay the amount indicated.

17 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	9 times a day	12 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 90% of the time	correct 85% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 14 days in the future	accurate up to 14 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 7 by 7 miles	to 30 by 30 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$15 more	$8 more
Check (✔) the box for the program you prefer →	☐	☐

18 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.
2. Make the improvements in the program I that chose above and pay the amount indicated.

19 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A	Program B
FREQUENCY OF UPDATES (Currently 4 times a day)	4 times a day	6 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 85% of the time	correct 80% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 7 days in the future	accurate up to 5 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 15 by 15 miles	to 30 by 30 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$8 more	$3 more
Check (✔) the box for the program you prefer →	☐	☐

20 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.

2. Make the improvements in the program I that chose above and pay the amount indicated.

21 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	9 times a day	12 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 80% of the time	correct 90% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 14 days in the future	accurate up to 10 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 15 by 15 miles	to 7 by 7 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$8 more	$15 more
Check (✔) the box for the program you prefer →	☐	☐

22 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.
2. Make the improvements in the program I that chose above and pay the amount indicated.

23 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	4 times a day	9 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 80% of the time	correct 95% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 10 days in the future	accurate up to 7 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 15 by 15 miles	to 7 by 7 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$24 more	$24 more
Check (✔) the box for the program you prefer ➔	☐	☐

24 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.

2. Make the improvements in the program I that chose above and pay the amount indicated.

25 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	12 times a day	4 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 95% of the time	correct 85% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 7 days in the future	accurate up to 10 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 3 by 3 miles	to 3 by 3 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$8 more	$3 more
Check (✔) the box for the program you prefer →	☐	☐

26 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.
2. Make the improvements in the program I that chose above and pay the amount indicated.

27 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	6 times a day	4 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 85% of the time	correct 95% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 7 days in the future	accurate up to 7 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 30 by 30 miles	to 15 by 15 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$3 more	$8 more
Check (✔) the box for the program you prefer ➔	☐	☐

28 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.

2. Make the improvements in the program I that chose above and pay the amount indicated.

29 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	Program B ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	12 times a day	6 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 95% of the time	correct 80% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 14 days in the future	accurate up to 7 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 7 by 7 miles	to 3 by 3 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$24 more	$15 more
Check (✔) the box for the program you prefer →	❑	❑

30 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.
2. Make the improvements in the program I that chose above and pay the amount indicated.

31 **If you had to choose, would you prefer Program A or Program B?** *Check one box at the bottom.*

	Program A ▼	**Program B** ▼
FREQUENCY OF UPDATES (Currently 4 times a day)	12 times a day	12 times a day
ACCURACY OF ONE-DAY FORECASTS (Currently correct about 80% of the time)	correct 90% of the time	correct 90% of the time
ACCURACY OF MULTIDAY FORECASTS (Currently accurate up to 5 days into the future)	accurate up to 10 days in the future	accurate up to 14 days in the future
GEOGRAPHIC DETAIL (Currently to 30 by 30 miles)	to 3 by 3 miles	to 15 by 15 miles
ADDED YEARLY COST TO YOUR HOUSEHOLD	$15 more	$24 more
Check (✔) the box for the program you prefer ➔	☐	☐

32 **Would you rather the NWS continue with current weather forecast technologies at current budget levels or would you rather have the program you chose above (A or B)?** *Circle the number indicating your preference.*

1. I would rather have no change in weather forecasting and no increase in costs to my household than have the program that I chose above.

2. Make the improvements in the program I that chose above and pay the amount indicated.

A Specific Program to Improve Weather Forecasting

33 **Now consider the following specific weather forecasting improvement program involving a combination of new satellites, radar, computers, computer programs, and weather service personnel. This specific program would improve the weather forecast as indicated in the following table:**

	CURRENT	WITH IMPROVEMENT PROGRAM
FREQUENCY OF UPDATES	4 times a day	4 times a day
ACCURACY OF ONE-DAY FORECASTS	80% correct	95% correct
ACCURACY OF MULTIDAY FORECASTS	Accurate up to 5 days into the future	Accurate up to 14 days into the future
GEOGRAPHIC DETAIL	Detail within 30 by 30 miles	Detail within 7 by 7 miles

If this improved program were the only program that the NWS was considering, what is the most your household would be willing to pay each year, in addition to what you are now paying? Remember that this annual payment would continue as long the improvements in weather forecasts were maintained. *Circle the dollar amount indicating the **most** your household would be willing to pay each year.*

$0	$1	$2	$3	$4	$6
$8	$11	$14	$17	$21	$26
$31	$37	$43	$49	$56	$64
$73	$83	$94	$100		

Other $__________

34 **Below are some reasons why people choose the amounts they do when answering the previous question (Question 33). Please rate each reason based on how much it influenced your answer of how much you would be willing to pay.** *Circle the number of your answer for each statement.*

	Did not influence my answer at all	Influenced my answer a little	Somewhat influenced my answer	Moderately influenced my answer	Greatly influenced my answer
I cannot afford to pay more for better weather forecasts	1	2	3	4	5
I should not have to pay for weather forecasts	1	2	3	4	5
I feel that it would useful to me to have improved weather forecasts	1	2	3	4	5
I believe it is important to carry out the weather forecasting improvements . . .	1	2	3	4	5
I don’t believe that the program will work or that the program described will ever happen . . .	1	2	3	4	5
I believe it is my responsibility to pay for the improvement program	1	2	3	4	5
I think the private sector should take over all weather forecasting	1	2	3	4	5
I wouldn’t be affected by the program as I don’t really use weather forecasts	1	2	3	4	5
I do not believe my money would actually be used for the improvement program	1	2	3	4	5
I need more information before committing any money	1	2	3	4	5
I believe that weather forecasts are good enough now and that improvements are not necessary	1	2	3	4	5

35 **Some people tell us it is difficult to think about paying to improve just the forecasts for normal weather. Would you say that the dollar amount you stated your household would be willing to pay for the weather forecasting improvement program (Q33) is:** *Circle the number of your answer.*

1. Just for improvements in weather forecasting under normal weather conditions (***go to Q37***)
2. Somewhat for improvements in weather forecasting under normal weather conditions and somewhat for improvements in severe weather forecasts (e.g., tornados, winter storms) (***go to Q36***).
3. Basically a contribution to all worthwhile public causes (***go to Q36***).
4. Other (*please specify*) ______________________ (***go to Q36***)

36 **About what percent of your dollar amount in Q33 would you like to see allocated just for the improvements in weather forecasting under normal weather conditions?** *Circle the number of your answer.*

None — All

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

37 **When you chose between Program A and B, or decided how much you would be willing to pay in Question 33, how important were each of the features of the programs?** *Circle the number of your answer for each item.*

	Not at all important	A little important	Somewhat important	Moderately important	Very important
Frequency of updated forecasts	1	2	3	4	5
Accuracy of one-day forecasts	1	2	3	4	5
Accuracy of multiday forecasts	1	2	3	4	5
Geographic detail	1	2	3	4	5
Yearly cost to your household	1	2	3	4	5

38 **Overall, how confident do you feel about the choices you made between Programs A and B in Questions 15 through 32 and the amount you indicated you would be willing to pay in Question 33?** *Circle the number of your answer.*

Not at all confident	A little confident	Somewhat confident	Fairly confident	Very confident
1	2	3	4	5

39 **The answers to the choice questions and Question 33 will provide citizen input to decision makers to be considered along with information from scientists and planners. With this in mind, how much do you think that your answers to the choice questions and Question 33 represent what you would like the NWS to do to improve weather forecasting technology?** *Circle the number of your answer.*

Do not represent my desires at all	Represent my desires a little	Represent my desires somewhat	Represent my desires fairly well	Represent my desires completely
1	2	3	4	5

You and Your Household

This information is used to help group your responses with responses of other households. Your individual responses and your name will not be released.

H1 **How long have you lived in the area where you currently live (say within 60 miles of your house)?**

____________ years

H2 **Your gender:** 1 Female

2 Male

H3 **Your age:** ____________ years old

H4 **How many people are there in your household, including yourself?**

____________ (number)

H5 **What is the highest degree or level of school you have completed?** *Circle the number of your answer.*

1 Did not complete high school
2 High school diploma or equivalent
3 Some college, two year college degree or technical school *(for example: AA, AS)*
4 Four year college graduate *(for example: BA, AB, BS)*
5 Master's degree *(for example: MA, MS, MEng, MEd, MSW, MBA)*
6 Professional degree or doctorate *(for example: MD, DDS, DVM, LLB, JD, PhD, EdD)*

H6 **What is you present employment status?** *Circle the numbers of all that apply to you.*

1 Employed full time
2 Employed part time
3 Retired
4 Homemaker
5 Student
6 Unemployed

H7 **On average, year round, what percent of your on-the-job time (e.g., the time that you are paid for working) is spent outdoors?** *Circle the number of the appropriate answer.*

None of my time — All of my time

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

H8 **On average, year round, how many hours per week do you spend traveling outside to and from work or school in a mode that could be affected by the weather?**

____________ Hours a week

H9 **On average, year round, what percent of your leisure time is spent outdoors?** *Circle the number of the appropriate answer.*

None of my time — All of my time

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

H10 **On average, year round, how many hours per week do you spend working outside in your yard or garden, washing your car, working on the house, or other activities "around the house"?**

_____ Hours a week

H11 **Which of the following categories best describes your race?** *Circle all that apply.*

1 White

2 Black or African American

3 Spanish/Hispanic/Latino

4 Asian or Pacific Islander

5 American Indian or Alaska Native

6 Other: ____

H12 **What was your total household income (before taxes) in 2000?** *Circle the number of your answer.*

1 less than $10,000

2 $10,000 to $19,999

3 $20,000 to $29,999

4 $30,000 to $39,999

5 $40,000 to $49,999

6 $50,000 to $59,999

7 $60,000 to $69,999

8 $70,000 to $79,999

9 $80,000 to $89,999

10 $90,000 to $99,999

11 $100,000 to $119,999

12 $120,000 to $139,999

13 $140,000 to 159,999

14 $160,000 or more

BEFORE CONTINUING

AT THIS TIME PLEASE LOOK BACK THROUGH THIS BOOKLET AND MAKE SURE YOU HAVE ANSWERED ALL OF THE QUESTIONS UP TO THIS POINT.

When you have completed all of the questions up to this point, please continue with the next section.

Once you start the next set of questions, please do not go back and change any answers to the questions in the first half of this booklet.

Please continue on the next page ☞

Other Weather Related Information

O1 **In the first part of this survey we discussed only the normal weather observations and forecasts provided by the NWS. In addition to these normal weather observations and forecasts, the NWS and the federal government also provide forecast information on:**

- **severe weather forecasts including watches and warnings**
- **forecasts used for aviation and marine commerce**
- **information provided to private weather services.**

Thinking now about all of the forecast information services provided by the NWS listed above, how important to you are weather forecasts for all types of weather related activities? *Circle the number of your answer.*

Not at all important	A little important	Somewhat important	Moderately important	Very important
1	2	3	4	5

O2 **All of the activities of the NWS are paid for through taxes as a part of the federal government. This money pays for all of the observation equipment (such as satellites and radar), analysis, and reporting activities of the NWS. As discussed above, in addition to normal weather observations and forecasts, the NWS provides services such as severe weather forecasts, including watches and warnings, forecasts used for aviation and marine commerce, and information provided to private weather services.**

Suppose that you were told that about $10 a year of your household's taxes went to paying for all of the weather forecasting services of the NWS and the federal government. Do you feel that the services you receive from the activities of the NWS are worth more than, less than, or exactly $10 a year to your household? *Circle the number of your answer.*

1. Currently worth less than $10 a year to my household
2. Currently worth $10 a year to my household
3. Currently worth more than $10 a year to my household

O3 **We now ask about severe weather events that may affect you. For the area where you live and work, how important is it to you personally to receive weather information about each of the severe weather events listed below?** *Circle the number of your answer for each item.*

	Not at all important	A little important	Somewhat important	Moderately important	Very important	Don't Know
Thunderstorms	1	2	3	4	5	8
Extreme heat	1	2	3	4	5	8
Extreme cold	1	2	3	4	5	8
Fog or low clouds . .	1	2	3	4	5	8
Lightning	1	2	3	4	5	8
Hurricanes	1	2	3	4	5	8
Tornadoes	1	2	3	4	5	8
Wind storms	1	2	3	4	5	8
Fire danger/drought	1	2	3	4	5	8
Flash floods	1	2	3	4	5	8
Snow or ice storms .	1	2	3	4	5	8
Hail	1	2	3	4	5	8
Air quality (smog/ ozone/particles) . . .	1	2	3	4	5	8
Other (*please describe*_________)	1	2	3	4	5	8

O4 **WATCHES and WARNINGS usually deal with expected severe weather events a few minutes to 12 hours in advance (depending on the type of weather event). For where you live, how accurate do you think forecasters are at predicting these events in advance (how good are forecasters at issuing WATCHES and WARNINGS)?** *Circle the number of your answer for each item.*

	Not at all accurate	A little accurate	Somewhat accurate	Moderately accurate	Very accurate	Don't Know
Thunderstorms . . .	1	2	3	4	5	8
Extreme heat	1	2	3	4	5	8
Extreme cold	1	2	3	4	5	8
Fog or low clouds .	1	2	3	4	5	8
Lightning	1	2	3	4	5	8
Hurricanes	1	2	3	4	5	8
Tornadoes	1	2	3	4	5	8
Wind storms	1	2	3	4	5	8
Fire danger/drought	1	2	3	4	5	8
Flash floods	1	2	3	4	5	8
Snow or ice storms	1	2	3	4	5	8
Hail	1	2	3	4	5	8
Air quality (smog/ ozone/particles) . . .	1	2	3	4	5	8
Other (*please describe* ________)	1	2	3	4	5	8

O5 **Of all of the possible severe or extreme weather conditions listed in the question above, which one event type would you most like to see more effort put into to improve forecasting abilities?**

____

Please briefly explain why this would be important to you?

____

____

O6 **Is there anything we have overlooked? Please use this space for any additional comments you would like to make.**

Your Participation Is Greatly Appreciated!

Ver. 1

APPENDIX C
CHOICE SET DESIGN

C.1 D-EFFICIENCY

Choice set design has not been thoroughly addressed in the nonmarket valuation stated preference literature. The basic goal of choice set design is to present individuals with a set of alternatives to choose between that will best allow the researcher to derive the individuals' preferences over the attributes. One statistical measure of this is "orthogonality," which indicates the ability to use statistical methods to separately identify individuals' responses to the different attributes. While orthogonality is one quality of a "good" choice set, other choice set design qualities need to be balanced with orthogonality. Huber and Zwerina (1996) discuss these other attributes: level balance, minimal overlap, and utility balance.

An overall measure of the efficiency of choice set design combines these qualities into a single measure. D-error is a measure of the efficiency of choice sets in "balancing" these qualities. When these qualities are jointly satisfied, a choice set design has minimal D-error. D-error, or D-efficiency, is thus often used as a measure of the overall quality of a choice set design from a purely statistical perspective. Experience in choice set design has shown that human fine-tuning of choice sets is often beneficial to ensure that the choices offered respondents are credible.

D-error can be used to compare choice sets within a particular design situation. It is not used to compare choice set designs between different situations where the number of levels or number of attributes differs.

C.2 CHOICE SET DESIGN

The *candidate choice set* represents all possible combinations of attribute levels that could comprise a single *choice question*. A *choice set design* consists of choice questions composed of several alternatives, each defined as combinations of different levels of the attributes (e.g., frequency of updates, one-day and multiday forecast accuracy, geographic detail, and yearly household cost).

With 20 versions of the survey, where each version has one example and eight complex (unrestricted) choice sets, we need a total of 20 examples and 160 complex choice sets. Treating cost separately, with four attributes in each alternative and two alternatives in each choice set there are a total of eight attributes in each choice set. With eight attributes, each with four levels, there are 65,536 (4^8) possible choice questions in the candidate choice set. As it is unwieldy to derive the optimal choice set from this size of a candidate set, we used SAS Proc Factex to create a resolution five candidate set. A resolution five candidate set allows the estimation of all main effects and two-way interactions between attributes (Kuhfeld, 1996). We first generated a resolution five candidate choice set that initially has 1024, points from which we identify and remove trivial points and identify and remove examples.

A trivial choice set is one in which we anticipate that all attribute levels of one alternative are equal or better than all attribute levels of another choice and thus should be chosen by 100% of respondents (barring any mistakes). An example choice set is one in which only one attribute in each alternative is different from the base level and the attribute that changes is different between the two alternatives. In other words, an "example" involves an individual making a direct comparison between two and only two attributes. We use only example type choice questions in the "example" question, Question 15. Eliminating trivial and examples from the resolution five candidate set left 714 points of "complex" choice sets.

From these 714 points we used Proc Optex to conduct a search for a D-optimal choice set comprised of 160 "complex" alternative pairs. An initial search using 25 random starting points (seeds) with 100 iterations each was used to find an optimal starting point. Several of the random starts iterated to the same D-efficiency, and thus we feel we have most likely achieved an optimal efficiency given the constraint of using 160 choice questions from the candidate set. Once one seed number was selected based on a review of the various optimality measures, primarily the D-efficiency measure, we re-ran Proc Optex with 5000 iterations to select the 160 choice pairs. Table C-1 shows the various efficiency measures for the final 160 point choice set design.

Table C-1
Efficiency Measures for Final 160 Point Choice Set Design

D-Efficiency	A-Efficiency	G-Efficiency	Average Prediction Standard Error
40.6116	33.3467	95.2292	0.3757

To select the 20 "example" choice pairs, we next generated a full resolution candidate set with 65,536 points from which we identify and remove trivial points and then identify and save examples. Elimination of trivial and keeping examples left 108 points. There were not enough design points to conduct a "Proc Optex" search with the example data sets. Examples were chosen based on the amount of difference from baseline for the attributes that were allowed to vary in the example. For example, a potential example choice set that presented an increase of 15% in one-day accuracy was preferred over one that offered only an increase in one-day accuracy of 5%.

For the 20 examples and 160 complex choice pairs, costs were fit to the choice sets based on the parameter estimates from the Denver pretest, an error term was added, and costs were rounded to the levels to be used in the survey instrument ($3, $8, $15, and $24). For the 20 examples, the costs were set equal to each other so that this attribute did not differ within any one example choice set. In this manner we attempted to present costs for the alternatives that were reasonably close to what individuals may be willing to pay for the alternatives while still maintaining a random aspect to the costs offered in the choice sets. This should help maintain realism and consistency in the presentation of the choice sets.

The resulting 20 examples questions and 160 complex choice questions were blocked into 20 versions with one example and eight complex questions in each. The example questions became Question 15. The order of the complex choice questions within each block was randomized. These became Questions 17, 19, 21, 23, 25, 27, 29, and 31 in the survey. Appendix D contains the complete listing of the final choice set. Table C-2 shows the correlations between attribute levels in the choice questions. The largest correlation (absolute value) is 0.31, between Household Cost and One Day. This is unlikely to interfere with parameter estimation and, as is seen in empirical analysis, all parameters are estimated distinctly and of the expected sign except for "frequency."

Table C-2
Correlations between Choice Set Attribute Levels

Attribute Level	Freq	Oneday	Multiday	GeogAcc	Cost
Frequency of Updates	1.00				
Accuracy of One-Day Forecasts	0.01	1.00			
Accuracy of Multiday Forecasts	-0.01	-0.02	1.00		
Geographic Detail	0.03	0.02	0.03	1.00	
Household Cost	0.02	0.31	0.06	-0.09	1.00

C.3 DESIGN OF WILLINGNESS-TO-PAY ATTRIBUTE LEVELS

Design of the program levels for the willingness-to-pay question (Q33) was somewhat simpler in that it involved only one set of attribute levels and no dollar amount: the dollar amount is stated by the respondent. With four attributes each with four levels the full candidate set is 256 points with four variables (attributes). We used Proc Factex to create the full resolution five candidate set from which the baseline alternative is eliminated. Dropping the single baseline point leaves 255 points in the candidate set.

We then used SAS Proc Optex to conduct a search for an optimal seed for reducing this to a 20 point set with 25 randomly generated seeds and 100 iterations with each seed. Once we had selected an optimal seed value based on the efficiency criterion (primarily the D-efficiency measure), we again used Proc Optex with that starting seed and 1000 iterations to select the 20 points for the final WTP attribute sets. These were then randomly blocked into the 20 different versions of the survey. Table C-3 shows the combinations of levels offered in the different versions of the survey instrument.

Table C-3
Options Provided to Respondents for Q33

Survey Version		Frequency of Updates (times per day)	Accuracy of One-day Forecasts (percent of time correct)	Accuracy of Multiday Forecasts (number of days into the future)	Geographic Detail (miles x miles)
All	**Current**	**4**	**80**	**5**	**30 x 30**
1	With improvements	4	95	14	7 x 7
2	With improvements	12	80	14	3 x 3
3	With improvements	6	80	5	30 x 30
4	With improvements	6	90	14	15 x 15
5	With improvements	4	80	7	15 x 15
6	With improvements	6	85	10	7 x 7
7	With improvements	4	85	5	15 x 15
8	With improvements	9	95	5	3 x 3
9	With improvements	6	90	7	7 x 7
10	With improvements	6	85	7	3 x 3
11	With improvements	9	85	14	30 x 30
12	With improvements	12	95	7	30 x 30
13	With improvements	12	85	10	15 x 15
14	With improvements	6	95	10	15 x 15
15	With improvements	9	90	7	15 x 15
16	With improvements	12	90	5	7 x 7
17	With improvements	4	85	7	7 x 7
18	With improvements	9	80	10	7 x 7
19	With improvements	4	90	10	3 x 3
20	With improvements	4	90	10	30 x 30

Table C-4 shows the attribute correlation matrix for the WTP question attribute sets.

Table C-4
Correlations between WTP Attribute Levels

Attribute Level	Freq	Oneday	Multiday	GeogAcc
Frequency of updates	1.000			
Accuracy of one-day forecasts	0.000	1.000		
Accuracy of multiday forecasts	0.024	0.000	1.000	
Geographic detail	0.043	0.000	0.007	1.000

Appendix D
Choice Sets

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
1	15	4	80	5	3	3	12	80	5	30	3
1	17	9	90	14	7	15	12	85	14	30	8
1	19	4	85	7	15	8	6	80	5	30	3
1	21	9	80	14	15	8	12	90	10	7	15
1	23	4	80	10	15	24	9	95	7	7	24
1	25	12	95	7	3	8	4	85	10	3	3
1	27	6	85	7	30	3	4	95	7	15	8
1	29	12	95	14	7	24	6	80	7	3	15
1	31	12	90	10	3	15	12	90	14	15	24
2	15	12	80	5	30	15	4	95	5	30	15
2	17	6	85	10	7	8	9	85	5	15	3
2	19	4	90	7	30	3	6	85	10	3	8
2	21	12	90	14	3	15	4	95	14	30	15
2	23	12	95	7	30	24	12	85	10	30	24
2	25	9	85	10	7	15	12	80	5	7	8
2	27	6	80	7	15	15	9	90	7	30	24
2	29	9	95	5	3	8	6	90	10	3	3
2	31	4	80	5	7	3	12	95	14	15	8
3	15	4	80	10	30	15	12	80	5	30	15
3	17	4	90	7	15	24	4	85	10	7	24
3	19	6	85	5	15	3	6	80	14	3	8
3	21	6	85	14	30	3	4	90	10	30	8
3	23	9	95	7	3	8	12	80	7	15	3
3	25	12	85	5	7	15	6	95	14	7	24
3	27	6	95	10	3	24	9	95	5	30	15
3	29	9	80	14	7	15	6	85	7	7	8
3	31	4	80	10	30	8	12	95	7	3	15
4	15	12	80	5	30	15	4	80	14	30	15
4	17	9	95	5	3	8	12	95	14	7	15
4	19	9	90	14	7	8	9	90	5	3	3
4	21	4	80	7	3	3	6	90	14	15	8
4	23	6	80	10	15	24	6	90	10	30	24

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
4	25	12	85	14	15	3	6	95	5	15	8
4	27	6	90	5	7	24	12	85	7	7	15
4	29	12	95	14	7	15	6	80	7	3	8
4	31	12	85	10	30	15	9	85	14	7	24
5	15	4	95	5	30	3	4	80	14	30	3
5	17	4	85	7	7	24	12	95	14	30	24
5	19	6	80	10	30	3	6	85	7	7	8
5	21	9	90	14	15	24	4	85	14	3	15
5	23	4	90	5	15	15	9	95	7	30	24
5	25	6	80	5	7	3	12	80	10	15	8
5	27	12	90	10	30	8	6	85	5	15	3
5	29	4	95	7	3	8	9	90	5	7	3
5	31	12	85	10	15	15	6	80	10	7	8
6	15	4	80	14	30	3	9	80	5	30	3
6	17	4	95	10	7	8	6	85	5	30	3
6	19	9	85	5	3	3	12	90	5	15	8
6	21	12	95	14	15	8	12	95	10	3	3
6	23	6	85	5	3	24	4	90	7	3	24
6	25	12	85	10	30	15	9	85	14	7	24
6	27	9	95	7	3	24	12	80	7	15	15
6	29	6	80	14	7	3	6	95	10	7	8
6	31	6	90	7	30	8	9	80	7	15	3
7	15	4	90	5	30	3	4	80	5	3	3
7	17	4	90	7	30	15	6	85	10	3	24
7	19	9	85	5	15	15	9	80	10	15	8
7	21	9	85	10	7	3	4	90	10	30	8
7	23	4	90	10	3	24	9	95	14	7	24
7	25	6	80	14	3	8	12	85	5	15	3
7	27	12	90	5	7	24	4	90	7	30	15
7	29	12	95	14	7	8	6	80	7	3	3
7	31	9	95	7	15	8	12	85	5	7	3
8	15	4	95	5	30	24	4	80	5	3	24

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
8	17	6	95	7	7	15	4	95	14	15	24
8	19	4	80	7	7	3	9	95	10	15	8
8	21	4	85	10	15	24	6	90	7	7	24
8	23	6	90	14	30	24	12	90	7	3	24
8	25	9	85	5	3	3	9	85	14	7	8
8	27	12	95	5	15	24	9	90	5	7	15
8	29	12	80	10	3	15	4	85	10	30	15
8	31	6	90	14	30	8	4	80	14	15	3
9	15	4	80	14	30	15	12	80	5	30	15
9	17	6	85	14	3	3	12	90	10	3	8
9	19	6	95	10	15	24	4	95	5	7	24
9	21	12	90	7	7	15	9	80	10	7	8
9	23	9	80	7	30	3	6	85	14	30	8
9	25	9	85	14	30	24	9	85	5	15	15
9	27	4	95	5	15	8	6	90	7	30	3
9	29	6	90	10	7	8	12	80	10	3	3
9	31	12	80	10	3	15	9	80	14	15	24
10	15	4	80	5	3	3	4	80	14	30	3
10	17	4	85	7	7	15	6	90	10	15	24
10	19	9	90	10	3	24	4	95	5	3	24
10	21	12	80	7	15	3	4	90	10	15	8
10	23	12	85	5	7	8	9	85	7	30	3
10	25	9	90	10	3	8	6	80	14	30	3
10	27	6	95	5	30	3	6	90	14	7	8
10	29	12	85	14	30	15	12	85	10	7	15
10	31	9	80	10	7	15	9	80	7	3	8
11	15	9	80	5	30	15	4	80	5	3	15
11	17	12	85	7	7	15	9	90	14	3	24
11	19	6	95	10	15	24	6	80	14	15	15
11	21	4	85	10	30	3	4	90	7	3	8
11	23	4	85	14	3	8	4	95	7	15	15
11	25	6	95	14	15	8	9	85	14	30	3

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
11	27	9	80	7	3	8	4	80	10	7	3
11	29	6	80	7	7	24	12	95	5	7	24
11	31	9	90	5	30	3	6	95	10	30	8
12	15	4	80	14	30	3	4	80	5	3	3
12	17	9	85	5	15	8	9	80	10	15	3
12	19	6	80	10	15	3	4	85	7	3	8
12	21	4	95	10	7	24	4	90	14	3	15
12	23	12	90	7	30	3	12	90	5	7	3
12	25	4	95	14	3	8	6	85	7	15	3
12	27	6	85	14	15	3	12	95	14	30	8
12	29	6	80	7	3	3	9	95	5	3	8
12	31	9	90	5	30	24	6	95	10	30	24
13	15	12	80	5	30	3	4	80	5	3	3
13	17	4	95	10	30	15	9	90	14	15	24
13	19	12	95	7	3	24	4	85	10	3	15
13	21	6	90	14	3	8	12	80	14	7	8
13	23	9	90	10	7	15	6	95	5	7	24
13	25	12	80	5	30	8	9	95	10	15	15
13	27	12	85	5	7	8	9	85	7	30	8
13	29	6	90	7	15	8	12	80	7	30	3
13	31	9	80	14	15	3	6	95	14	3	8
14	15	4	80	5	3	3	4	90	5	30	3
14	17	12	90	10	3	8	6	95	10	30	8
14	19	9	80	7	15	15	4	85	14	15	24
14	21	6	95	5	30	8	6	90	14	7	15
14	23	6	85	7	7	15	12	80	10	30	8
14	25	9	90	14	30	24	4	90	5	15	24
14	27	6	90	5	3	8	9	85	7	3	3
14	29	9	95	10	30	3	9	95	7	15	3
14	31	4	80	14	7	3	12	85	10	3	8
15	15	12	80	5	30	3	4	80	5	7	3
15	17	12	85	14	15	8	4	80	14	7	3

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
15	19	6	90	10	30	8	6	80	10	15	3
15	21	6	85	7	3	24	6	90	5	3	24
15	23	12	90	7	3	15	9	95	7	30	15
15	25	9	80	5	7	15	12	90	7	15	24
15	27	9	95	10	15	8	9	80	10	3	3
15	29	6	95	5	7	24	9	85	5	3	24
15	31	4	85	14	30	3	12	95	7	7	8
16	15	4	80	5	7	15	4	80	14	30	15
16	17	6	90	10	3	8	9	80	10	7	3
16	19	6	85	14	3	24	9	85	7	30	15
16	21	4	95	14	7	8	9	80	5	15	3
16	23	12	90	5	3	8	6	90	7	15	8
16	25	9	80	7	15	15	6	90	5	7	24
16	27	9	85	10	7	3	4	90	10	30	8
16	29	9	85	10	30	15	4	95	14	3	24
16	31	12	95	5	15	8	12	85	14	15	8
17	15	4	95	5	30	3	4	80	5	7	3
17	17	6	85	7	30	8	4	95	7	15	15
17	19	4	80	5	3	15	6	85	7	7	24
17	21	12	90	10	3	3	12	90	14	15	8
17	23	12	80	7	7	3	6	95	14	3	8
17	25	6	85	7	7	15	4	90	5	7	24
17	27	4	95	14	15	24	9	90	10	30	15
17	29	12	95	14	30	24	9	95	10	7	24
17	31	9	90	5	15	8	12	85	5	3	3
18	15	4	95	5	30	3	12	80	5	30	3
18	17	6	85	10	3	24	12	85	5	30	15
18	19	12	80	10	15	24	12	90	7	15	24
18	21	4	90	7	15	15	4	85	10	7	8
18	23	12	85	14	15	8	6	95	5	15	15
18	25	9	95	7	30	8	4	80	7	7	3
18	27	9	85	7	3	15	6	80	14	3	15

Table D-1
Table of Choice Sets

Ver.	Q.	FreqA	OneDayA	MultiDayA	GeogAccA	CostA	FreqB	OneDayB	MultiDayB	GeogAccB	CostB
18	29	4	90	5	7	24	9	85	14	15	24
18	31	9	80	14	30	3	9	90	10	3	8
19	15	4	80	5	3	3	4	95	5	30	3
19	17	9	90	14	7	24	4	95	7	7	24
19	19	4	85	14	3	8	6	80	10	7	3
19	21	9	80	7	30	8	6	85	14	30	15
19	23	6	90	5	15	24	4	85	7	15	24
19	25	6	95	5	7	3	6	95	10	15	8
19	27	4	85	10	15	3	12	95	5	3	8
19	29	9	95	7	30	8	12	90	14	30	3
19	31	12	90	7	15	15	9	90	5	3	15
20	15	4	80	14	30	3	4	95	5	30	3
20	17	4	90	7	15	15	9	80	14	3	8
20	19	4	85	5	3	15	12	95	10	15	24
20	21	12	80	10	7	3	4	90	7	7	8
20	23	9	95	10	15	24	12	95	7	30	24
20	25	4	90	14	7	8	6	85	5	15	3
20	27	12	85	7	30	8	12	80	7	3	3
20	29	6	80	14	3	3	9	90	14	7	8
20	31	6	95	10	7	24	4	85	10	3	15

APPENDIX E
CHOICE QUESTION FREQUENCIES BY VERSION

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q15		Q15		Q15		Q15		Q15	
Ver.	1		2		3		4		5	
Freq.	17	5	0	16	15	6	5	15	16	2
%	77.3	22.7	0.0	100.0	71.4	28.6	25.0	75.0	88.9	11.1
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q16		Q16		Q16		Q16		Q16	
Ver.	1		2		3		4		5	
Freq.	11	11	10	6	13	8	9	11	7	11
%	50.0	50.0	62.5	37.5	61.9	38.1	45.0	55.0	38.9	61.1
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q17		Q17		Q17		Q17		Q17	
Ver.	1		2		3		4		5	
Freq.	12	10	4	12	10	11	10	10	10	8
%	54.5	45.5	25.0	75.0	47.6	52.4	50.0	50.0	55.6	44.4
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q18		Q18		Q18		Q18		Q18	
Ver.	1		2		3		4		5	
Freq.	13	9	9	7	12	9	8	12	12	6
%	59.1	40.9	56.3	43.8	57.1	42.9	40.0	60.0	66.7	33.3
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q19		Q19		Q19		Q19		Q19	
Ver.	1		2		3		4		5	
Freq.	13	9	14	2	13	8	12	8	7	11
%	59.1	40.9	87.5	12.5	61.9	38.1	60.0	40.0	38.9	61.1
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q20		Q20		Q20		Q20		Q20	
Ver.	1		2		3		4		5	
Freq.	12	10	7	9	8	13	8	12	8	10
%	54.5	45.5	43.8	56.3	38.1	61.9	40.0	60.0	44.4	55.6
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q21		Q21		Q21		Q21		Q21	
Ver.	1		2		3		4		5	
Freq.	12	10	9	7	13	8	5	15	6	12
%	54.5	45.5	56.3	43.8	61.9	38.1	25.0	75.0	33.3	66.7

	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q22		Q22		Q22		Q22		Q22	
Ver.	1		2		3		4		5	
Freq.	12	10	10	6	11	10	5	15	11	7
%	54.5	45.5	62.5	37.5	52.4	47.6	25.0	75.0	61.1	38.9
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q23		Q23		Q23		Q23		Q23	
Ver.	1		2		3		4		5	
Freq.	5	17	13	3	14	7	4	16	14	4
%	22.7	77.3	81.3	18.8	66.7	33.3	20.0	80.0	77.8	22.2
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q24		Q24		Q24		Q24		Q24	
Ver.	1		2		3		4		5	
Freq.	16	6	12	4	10	11	12	8	10	8
%	72.7	27.3	75.0	25.0	47.6	52.4	60.0	40.0	55.6	44.4
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q25		Q25		Q25		Q25		Q25	
Ver.	1		2		3		4		5	
Freq.	9	13	8	8	8	13	11	9	14	4
%	40.9	59.1	50.0	50.0	38.1	61.9	55.0	45.0	77.8	22.2
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q26		Q26		Q26		Q26		Q26	
Ver.	1		2		3		4		5	
Freq.	10	12	10	6	11	10	7	13	10	8
%	45.5	54.5	62.5	37.5	52.4	47.6	35.0	65.0	55.6	44.4
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q27		Q27		Q27		Q27		Q27	
Ver.	1		2		3		4		5	
Freq.	10	12	9	7	12	9	7	13	6	12
%	45.5	54.5	56.3	43.8	57.1	42.9	35.0	65.0	33.3	66.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q28		Q28		Q28		Q28		Q28	
Ver.	1		2		3		4		5	
Freq.	13	9	12	4	13	8	14	6	8	10
%	59.1	40.9	75.0	25.0	61.9	38.1	70.0	30.0	44.4	55.6

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q29		Q29		Q29		Q29		Q29	
Ver.	1		2		3		4		5	
Freq.	10	12	3	13	4	17	13	7	12	6
%	45.5	54.5	18.8	81.3	19.0	81.0	65.0	35.0	66.7	33.3
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q30		Q30		Q30		Q30		Q30	
Ver.	1		2		3		4		5	
Freq.	16	6	7	9	13	8	7	13	7	11
%	72.7	27.3	43.8	56.3	61.9	38.1	35.0	65.0	38.9	61.1
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q31		Q31		Q31		Q31		Q31	
Ver.	1		2		3		4		5	
Freq.	18	4	9	7	9	12	10	10	4	14
%	81.8	18.2	56.3	43.8	42.9	57.1	50.0	50.0	22.2	77.8
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q32		Q32		Q32		Q32		Q32	
Ver.	1		2		3		4		5	
Freq.	14	8	8	8	12	9	13	7	10	8
%	63.6	36.4	50.0	50.0	57.1	42.9	65.0	35.0	55.6	44.4
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q15		Q15		Q15		Q15		Q15	
Ver.	6		7		8		9		10	
Freq.	10	5	11	7	18	2	15	6	9	11
%	66.7	33.3	61.1	38.9	90.0	10.0	71.4	28.6	45.0	55.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q16		Q16		Q16		Q16		Q16	
Ver.	6		7		8		9		10	
Freq.	7	8	4	14	9	11	12	9	10	10
%	46.7	53.3	22.2	77.8	45.0	55.0	57.1	42.9	50.0	50.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q17		Q17		Q17		Q17		Q17	
Ver.	6		7		8		9		10	
Freq.	8	7	16	2	14	6	15	6	17	3
%	53.3	46.7	88.9	11.1	70.0	30.0	71.4	28.6	85.0	15.0

	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q18		Q18		Q18		Q18		Q18	
Ver.	6		7		8		9		10	
Freq.	4	11	10	8	8	12	8	13	16	4
%	26.7	73.3	55.6	44.4	40.0	60.0	38.1	61.9	80.0	20.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q19		Q19		Q19		Q19		Q19	
Ver.	6		7		8		9		10	
Freq.	11	4	8	10	8	12	17	4	6	14
%	73.3	26.7	44.4	55.6	40.0	60.0	81.0	19.0	30.0	70.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q20		Q20		Q20		Q20		Q20	
Ver.	6		7		8		9		10	
Freq.	6	9	10	8	5	15	14	7	16	4
%	40.0	60.0	55.6	44.4	25.0	75.0	66.7	33.3	80.0	20.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q21		Q21		Q21		Q21		Q21	
Ver.	6		7		8		9		10	
Freq.	2	13	11	7	3	17	9	12	7	13
%	13.3	86.7	61.1	38.9	15.0	85.0	42.9	57.1	35.0	65.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q22		Q22		Q22		Q22		Q22	
Ver.	6		7		8		9		10	
Freq.	4	11	7	11	12	8	9	12	12	8
%	26.7	73.3	38.9	61.1	60.0	40.0	42.9	57.1	60.0	40.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q23		Q23		Q23		Q23		Q23	
Ver.	6		7		8		9		10	
Freq.	1	14	6	12	12	8	4	17	6	14
%	6.7	93.3	33.3	66.7	60.0	40.0	19.0	81.0	30.0	70.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q24		Q24		Q24		Q24		Q24	
Ver.	6		7		8		9		10	
Freq.	10	5	9	9	12	8	11	10	12	8
%	66.7	33.3	50.0	50.0	60.0	40.0	52.4	47.6	60.0	40.0

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q25		Q25		Q25		Q25		Q25	
Ver.	6		7		8		9		10	
Freq.	9	6	6	12	13	7	8	13	10	10
%	60.0	40.0	33.3	66.7	65.0	35.0	38.1	61.9	50.0	50.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q26		Q26		Q26		Q26		Q26	
Ver.	6		7		8		9		10	
Freq.	11	4	8	10	10	10	15	6	11	9
%	73.3	26.7	44.4	55.6	50.0	50.0	71.4	28.6	55.0	45.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q27		Q27		Q27		Q27		Q27	
Ver.	6		7		8		9		10	
Freq.	11	4	3	15	4	16	10	11	7	13
%	73.3	26.7	16.7	83.3	20.0	80.0	47.6	52.4	35.0	65.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q28		Q28		Q28		Q28		Q28	
Ver.	6		7		8		9		10	
Freq.	8	7	8	10	12	8	6	15	14	6
%	53.3	46.7	44.4	55.6	60.0	40.0	28.6	71.4	70.0	30.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q29		Q29		Q29		Q29		Q29	
Ver.	6		7		8		9		10	
Freq.	6	9	12	6	11	9	18	3	8	12
%	40.0	60.0	66.7	33.3	55.0	45.0	85.7	14.3	40.0	60.0
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q30		Q30		Q30		Q30		Q30	
Ver.	6		7		8		9		10	
Freq.	4	11	5	13	17	3	7	14	16	4
%	26.7	73.3	27.8	72.2	85.0	15.0	33.3	66.7	80.0	20.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q31		Q31		Q31		Q31		Q31	
Ver.	6		7		8		9		10	
Freq.	7	8	15	3	12	8	11	10	3	17
%	46.7	53.3	83.3	16.7	60.0	40.0	52.4	47.6	15.0	85.0

	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q32		Q32		Q32		Q32		Q32	
Ver.	6		7		8		9		10	
Freq.	4	11	7	11	7	13	15	6	14	6
%	26.7	73.3	38.9	61.1	35.0	65.0	71.4	28.6	70.0	30.0
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q15		Q15		Q15		Q15		Q15	
Ver.	11		12		13		14		15	
Freq.	6	13	8	14	5	14	4	12	4	13
%	31.6	68.4	36.4	63.6	26.3	73.7	25.0	75.0	23.5	76.5
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q16		Q16		Q16		Q16		Q16	
Ver.	11		12		13		14		15	
Freq.	11	8	10	12	7	12	8	8	8	9
%	57.9	42.1	45.5	54.5	36.8	63.2	50.0	50.0	47.1	52.9
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q17		Q17		Q17		Q17		Q17	
Ver.	11		12		13		14		15	
Freq.	11	8	4	18	18	1	4	12	7	10
%	57.9	42.1	18.2	81.8	94.7	5.3	25.0	75.0	41.2	58.8
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q18		Q18		Q18		Q18		Q18	
Ver.	11		12		13		14		15	
Freq.	11	8	11	11	8	11	10	6	8	9
%	57.9	42.1	50.0	50.0	42.1	57.9	62.5	37.5	47.1	52.9
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q19		Q19		Q19		Q19		Q19	
Ver.	11		12		13		14		15	
Freq.	6	13	14	8	5	14	7	9	6	11
%	31.6	68.4	63.6	36.4	26.3	73.7	43.8	56.3	35.3	64.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q20		Q20		Q20		Q20		Q20	
Ver.	11		12		13		14		15	
Freq.	12	7	12	10	9	10	12	4	8	9
%	63.2	36.8	54.5	45.5	47.4	52.6	75.0	25.0	47.1	52.9

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q21		Q21		Q21		Q21		Q21	
Ver.	11		12		13		14		15	
Freq.	7	12	3	19	17	2	11	5	4	13
%	36.8	63.2	13.6	86.4	89.5	10.5	68.8	31.3	23.5	76.5
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q22		Q22		Q22		Q22		Q22	
Ver.	11		12		13		14		15	
Freq.	8	11	15	7	6	13	10	6	14	3
%	42.1	57.9	68.2	31.8	31.6	68.4	62.5	37.5	82.4	17.6
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q23		Q23		Q23		Q23		Q23	
Ver.	11		12		13		14		15	
Freq.	13	6	9	13	11	8	9	7	5	12
%	68.4	31.6	40.9	59.1	57.9	42.1	56.3	43.8	29.4	70.6
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q24		Q24		Q24		Q24		Q24	
Ver.	11		12		13		14		15	
Freq.	10	9	10	12	10	9	11	5	9	8
%	52.6	47.4	45.5	54.5	52.6	47.4	68.8	31.3	52.9	47.1
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q25		Q25		Q25		Q25		Q25	
Ver.	11		12		13		14		15	
Freq.	14	5	13	9	6	13	13	3	8	9
%	73.7	26.3	59.1	40.9	31.6	68.4	81.3	18.8	47.1	52.9
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q26		Q26		Q26		Q26		Q26	
Ver.	11		12		13		14		15	
Freq.	7	12	12	10	6	13	12	4	12	5
%	36.8	63.2	54.5	45.5	31.6	68.4	75.0	25.0	70.6	29.4
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q27		Q27		Q27		Q27		Q27	
Ver.	11		12		13		14		15	
Freq.	2	17	15	7	10	9	10	6	12	5
%	10.5	89.5	68.2	31.8	52.6	47.4	62.5	37.5	70.6	29.4

	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q28		Q28		Q28		Q28		Q28	
Ver.	11		12		13		14		15	
Freq.	8	11	12	10	10	9	10	6	6	11
%	42.1	57.9	54.5	45.5	52.6	47.4	62.5	37.5	35.3	64.7
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q29		Q29		Q29		Q29		Q29	
Ver.	11		12		13		14		15	
Freq.	8	11	11	11	15	4	12	4	14	3
%	42.1	57.9	50.0	50.0	78.9	21.1	75.0	25.0	82.4	17.6
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q30		Q30		Q30		Q30		Q30	
Ver.	11		12		13		14		15	
Freq.	12	7	11	11	8	11	7	9	14	3
%	63.2	36.8	50.0	50.0	42.1	57.9	43.8	56.3	82.4	17.6
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q31		Q31		Q31		Q31		Q31	
Ver.	11		12		13		14		15	
Freq.	6	13	4	18	6	13	12	4	6	11
%	31.6	68.4	18.2	81.8	31.6	68.4	75.0	25.0	35.3	64.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q32		Q32		Q32		Q32		Q32	
Ver.	11		12		13		14		15	
Freq.	10	9	16	6	8	11	9	7	6	11
%	52.6	47.4	72.7	27.3	42.1	57.9	56.3	43.8	35.3	64.7
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q15		Q15		Q15		Q15		Q15	
Ver.	16		17		18		19		20	
Freq.	12	11	13	5	21	2	5	11	6	11
%	52.2	47.8	72.2	27.8	91.3	8.7	31.3	68.8	35.3	64.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q16		Q16		Q16		Q16		Q16	
Ver.	16		17		18		19		20	
Freq.	12	11	5	13	7	16	5	11	3	14
%	52.2	47.8	27.8	72.2	30.4	69.6	31.3	68.8	17.6	82.4

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q17		Q17		Q17		Q17		Q17	
Ver.	16		17		18		19		20	
Freq.	12	11	6	12	12	11	2	14	6	11
%	52.2	47.8	33.3	66.7	52.2	47.8	12.5	87.5	35.3	64.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q18		Q18		Q18		Q18		Q18	
Ver.	16		17		18		19		20	
Freq.	10	13	14	4	14	9	9	7	7	10
%	43.5	56.5	77.8	22.2	60.9	39.1	56.3	43.8	41.2	58.8
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q19		Q19		Q19		Q19		Q19	
Ver.	16		17		18		19		20	
Freq.	8	15	10	8	4	19	8	8	11	6
%	34.8	65.2	55.6	44.4	17.4	82.6	50.0	50.0	64.7	35.3
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q20		Q20		Q20		Q20		Q20	
Ver.	16		17		18		19		20	
Freq.	14	9	13	5	12	11	6	10	10	7
%	60.9	39.1	72.2	27.8	52.2	47.8	37.5	62.5	58.8	41.2
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q21		Q21		Q21		Q21		Q21	
Ver.	16		17		18		19		20	
Freq.	17	6	12	6	13	10	5	11	8	9
%	73.9	26.1	66.7	33.3	56.5	43.5	31.3	68.8	47.1	52.9
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q22		Q22		Q22		Q22		Q22	
Ver.	16		17		18		19		20	
Freq.	7	16	6	12	8	15	9	7	5	12
%	30.4	69.6	33.3	66.7	34.8	65.2	56.3	43.8	29.4	70.6
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q23		Q23		Q23		Q23		Q23	
Ver.	16		17		18		19		20	
Freq.	7	16	4	14	11	12	9	7	15	2
%	30.4	69.6	22.2	77.8	47.8	52.2	56.3	43.8	88.2	11.8

	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q24		Q24		Q24		Q24		Q24	
Ver.	16		17		18		19		20	
Freq.	9	13	10	8	8	15	9	7	9	8
%	40.9	59.1	55.6	44.4	34.8	65.2	56.3	43.8	52.9	47.1
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q25		Q25		Q25		Q25		Q25	
Ver.	16		17		18		19		20	
Freq.	12	11	10	8	15	8	6	10	8	9
%	52.2	47.8	55.6	44.4	65.2	34.8	37.5	62.5	47.1	52.9
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q26		Q26		Q26		Q26		Q26	
Ver.	16		17		18		19		20	
Freq.	16	7	15	3	10	13	8	8	5	12
%	69.6	30.4	83.3	16.7	43.5	56.5	50.0	50.0	29.4	70.6
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q27		Q27		Q27		Q27		Q27	
Ver.	16		17		18		19		20	
Freq.	11	12	11	7	15	8	11	5	6	11
%	47.8	52.2	61.1	38.9	65.2	34.8	68.8	31.3	35.3	64.7
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q28		Q28		Q28		Q28		Q28	
Ver.	16		17		18		19		20	
Freq.	8	15	14	4	12	11	6	10	10	7
%	34.8	65.2	77.8	22.2	52.2	47.8	37.5	62.5	58.8	41.2
	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q29		Q29		Q29		Q29		Q29	
Ver.	16		17		18		19		20	
Freq.	11	12	7	11	15	8	8	8	7	10
%	47.8	52.2	38.9	61.1	65.2	34.8	50.0	50.0	41.2	58.8
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q30		Q30		Q30		Q30		Q30	
Ver.	16		17		18		19		20	
Freq.	14	9	14	4	14	9	7	9	4	13
%	60.9	39.1	77.8	22.2	60.9	39.1	43.8	56.3	23.5	76.5

	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B	Chose A	Chose B
Q.	Q31		Q31		Q31		Q31		Q31	
Ver.	16		17		18		19		20	
Freq.	15	8	9	9	9	14	10	6	7	10
%	65.2	34.8	50.0	50.0	39.1	60.9	62.5	37.5	41.2	58.8
	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice	Do Nothing	Stay w. Choice
Q.	Q32		Q32		Q32		Q32		Q32	
Ver.	16		17		18		19		20	
Freq.	8	15	8	10	7	16	8	8	11	6
%	34.8	65.2	44.4	55.6	30.4	69.6	50.0	50.0	64.7	35.3

APPENDIX F
MODELING CONSUMER PREFERENCES FOR WEATHER FORECAST IMPROVEMENTS USING STATED CHOICE AND STATED VALUE DATA

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F.1 INTRODUCTION

The purpose of this research is to estimate the parameters of a conditional indirect utility function for improved weather forecasts using stated preference (SP) and stated value (SV) data. The SP data consist of the answers to choice questions. Each sampled individual indicated their choice between a pair of weather forecast improvement alternatives, and then indicated whether they prefer the chosen alternative or no improvement (do nothing). For each sampled individual, these two questions are repeated $J = 9$ times, where the improvements to characteristics of weather forecasts are varied over the J pairs. The SV data are consistent with the answer to a single willingness-to-pay (contingent valuation) question using a payment card where the program offered for valuation varied across the 20 different versions of the survey. Only one SV question was asked of each individual. A series of follow-up questions was implemented to address issues such as scenario rejection and embedding.

Section F.2 develops the choice probabilities for the two weather forecast improvement alternatives using only the part of the data that indicates which weather forecast improvement alternative is chosen (the A-B model). Section F.3 incorporates a random parameters model to account for the interdependency of responses coming from the same individual. Section F.4 uses all of the data to model whether the individual prefers the chosen alternative or to do nothing, given that he or she has already indicated a preference between the two weather forecast improvements (the A-B-Nothing model).

F.2 A BASIC MODEL OF BINARY CHOICE

Let utility for the various weather information alternatives, including the status quo, be given by

$$U_{ij}^{k_{ij}} = \beta_i' \mathrm{x}_{ij}^{k_{ij}} + \varepsilon_{ij}^{k_{ij}}, i = 1,\ldots,n, j = 1,\ldots J, k_{ij} = 1,2, \tag{F-1}$$

where $U_{ij}^{k_{ij}}$ is the utility of alternative k_{ij} chosen by individual i during occasion j.[1] That is, i indexes the $n = 381$ respondents, j indexes the $J = 9$ pairs, and k_{ij} indicates which of the two alternatives within each pair is chosen. The $L \times 1$ vector x_{ij} contains the observed characteristics of the alternatives, such as the frequency of forecasts and cost (possibly interacted with characteristics of the individual) and hence the elements of the unknown $L \times 1$ vector β can be interpreted as marginal utilities.

1. This notation, especially the use of k_{ij} to indicate either a 1 or a 2, is a bit cumbersome at first, but will make precise many of the concepts below.

The fifth element of $x_{ij}^{k_{ij}}$ is the difference between choice-occasion income for individual *i* and the cost of alternative k_{ij}, and the model is initially restricted to one with a constant marginal utility of money, which is the fifth element of β_i.[2] This specification implies no income effects; that is, the probability of choosing any alternative is independent of income. The term $\beta_i' x_{ij}^{k_{ij}}$ is the nonstochastic part of utility, and $\varepsilon_{ij}^{k_{ij}}$ represents a stochastic component.

The following assumptions characterize the basic model:

A1. $\beta_i = \beta$ for all *i*

A2. $\varepsilon_{ij}^{k_{ij}}$ are independent and identically distributed mean zero normal random variables, uncorrelated with x_{ij}, with constant unknown variance σ_ε^2.

Individuals are assumed to maximize utility at each choice occasion. The probability of choosing alternative 1, for example, is:

$$\begin{aligned} P_{ij}^1 &= P\left(\beta' x_{ij}^1 + \varepsilon_{ij}^1 > \beta' x_{ij}^2 + \varepsilon_{ij}^2\right) \\ &= P\left(\varepsilon_{ij}^2 - \varepsilon_{ij}^1 < -\beta'\left(x_{ij}^2 - x_{ij}^1\right)\right) \\ &= \Phi\left[-\beta'\left(x_{ij}^2 - x_{ij}^1\right)\big/\sqrt{2}\sigma_\varepsilon\right] \end{aligned} \qquad \text{(F-2)}$$

and similarly for alternative 2, where $\sqrt{2}\sigma_e$ is the standard deviation of $\varepsilon_{ij}^2 - \varepsilon_{ij}^1$ under assumption A2, and $\Phi(\cdot)$ is the univariate standard normal cumulative distribution function. Note that Equation F-2 comprises the usual probit model for dichotomous choice under the assumption the individual knows the random component and maximizes utility. The parameter vector β is identified only up to the scale factor $\sqrt{2}\sigma_e$, and σ_e is not identified, since only the sign and not the scale of the dependent variable (the utility difference) is observed. Nevertheless, we chose to list the parameters of the likelihood ($\beta, \sigma_\varepsilon$) function separately. σ_ε^2 is set at 0.5 for model identification.

Note also that the *J* observations for each respondent have simply been stacked to produce a data set with *Jn* observations. If individual characteristics are interacted with characteristics of the alternatives, these individual specific effects will allow observed choices across the *J*

2. Denoting Y_i as income and C_{ij} as the cost of alternative *j* to individual *i*, the term $(Y_j - C_{ij})$ is the fifth element of $x_{ij}^{k_{ij}}$. Because income does not vary across alternatives, Y_j does not appear in the choice probabilities.

observations for a given individual to be correlated, even though the $\varepsilon_{ij}^{k_{ij}}$ are, for now, assumed to be uncorrelated.

Under assumptions A1 and A2, the unit of observation is an *i*, *j* pair, so that the likelihood is the product of the *Jn* probabilities like Equation F-2:

$$L\left(k_{ij},\, i=1,\ldots,\, J \,\middle|\, x_{ij}^{1}, x_{ij}^{2},\, \beta, \sigma_{\varepsilon}\right) = \prod_{i=1}^{n}\prod_{j=1}^{J} P_{ij}^{k_{ij}}. \tag{F-3}$$

F.3 A RANDOM PARAMETERS MODEL

In this model the assumption of uncorrelated disturbances within pairs and across choice occasions is relaxed, in the spirit of Hausman and Wise (1978). Assumption A2 is maintained, but assumption A1 is now replaced by:

A1′. $\beta_i = \beta + v_i,\, v_i$ i.i.d $\sim N(\mathrm{O}, \Sigma)$, (F-4)

where v_i is an $L \times 1$ random vector that represents heterogeneity of preferences across individuals.[3] An individual's marginal utilities of alternative characteristics differs from the average by an additive, mean-zero random variable assumed uncorrelated with the model disturbance. He or she evaluates all *J* choice occasions with these marginal utilities. Then

$$U_{ij}^{k_{ij}} = \beta_i' x_{ij}^{k_{ij}} + \varepsilon_{ij}^{k_{ij}} = \beta_i' x_{ij}^{k_{ij}} + (v_i' x_{ij}^{k_{ij}} + \varepsilon_{ij}^{k_{ij}}), \tag{F-5}$$

where the new model disturbance is in parentheses. It is straightforward to find the correlation between these disturbances (and hence the utilities) within a pair and across pairings for each individual. Within a pair we have,

$$E\left[(v_i' x_{ij}^{1} + \varepsilon_{ij}^{1})\,(v_i' x_{ij}^{2} + \varepsilon_{ij}^{2})\right] = (x_{ij}^{1})'\,\Sigma(x_{ij}^{2}), \tag{F-6}$$

and from pair *j* to pair *l* we have

$$E\left[(v_i' x_{ij}^{1} + \varepsilon_{ij}^{k_{ij}})(v_i' x_{il}^{k_{il}} + \varepsilon_{il}^{k_{il}})\right] = (x_{ij}^{k_{ij}})'\;\Sigma(x_{il}^{k_{il}}). \tag{F-7}$$

3. This is the usual formulation for the random coefficients model. See Hildreth and Houck (1968), Swamy (1970), and Hsiao (1975).

In this specification, it now makes sense for the unit of observation to be the individual (*i*), not the individual-pair (*i, j*) as in the previous model. The generalization of equation is a *J*-dimensional multinormal probability:

$$P_i = P(k_{i1},\ldots,k_{iJ}) = P\left(U_{i1}^{k_{i1}} > U_{i1}^{3-k_{i1}},\ldots,U_{iJ}^{k_{iJ}} > U_{iJ}^{3-k_{iJ}}\right). \tag{F-8}$$

Although evaluation of this integral is more complicated than the equivalent expression in the basic model, the "equicorrelated" nature of the errors means that P_i can be calculated as the integral of a conditional probability and a density (the density of υ_i) by standard reasoning.[4] This is done below. For the model of Equation F-4, $\beta_i = \beta + \upsilon_i$, the likelihood of observing the *n* sets of $k_{i1}, \ldots, k_{iJ}$ is

$$L\left(k_{ij}, i=1,\ldots,n,\ j=1,\ldots,J \,\middle|\, x_{ij}^1, x_{ij}^2; \beta, \sigma_\varepsilon, \Sigma\right) = \prod_{i=1}^{n} P(k_{i1},\ldots,k_{iJ}). \tag{F-9}$$

The probability in the likelihood, $P(k_{i1}, \ldots, k_{iJ})$, is given by Equation F-8. Substituting the random utility model (Equation F-1) and the specification for the β_i (Equation F-4) into Equation F-8 yields, after some rearranging.

$$\begin{aligned} P_i &= P(k_{i1},\ldots,k_{iJ}) = \\ P\Big[&(\nu_i' x_{i1}^{3-k_{i1}} + \varepsilon_{i1}^{3-k_{i1}}) - (\nu_i' x_{i1}^{k_{i1}} + \varepsilon_{i1}^{k_{i1}}) < -\beta'(x_{i1}^{3-k_{i1}} - x_{i1}^{k_{i1}}), \\ &\vdots \\ &(\nu_i' x_{iJ}^{3-k_{iJ}} + \varepsilon_{iJ}^{3-k_{iJ}}) - (\nu_i' x_{iJ}^{k_{iJ}} + \varepsilon_{iJ}^{k_{iJ}}) < -\beta' x_{iJ}^{3-k_{iJ}} + x_{iJ}^{3-k_{iJ}}\Big] \end{aligned} \tag{F-10}$$

The *J* events are correlated, but the source of the correlation is the person-specific parameter error ν_i. This common-factor design allows for the computational simplification mentioned above. The *J* events in the probability in equation , conditional on ν_i, are independent, so the joint probability may be written as the product of the *J* conditional probabilities. Then the resulting product is integrated with respect to ν_i to undue the conditioning:

4. See Butler and Moffitt (1982), and Waldman (1985).

$$\begin{aligned}P_i = \int_{-\infty}^{\infty} P\Big[&\varepsilon_{i1}^{3-k_{i1}} - \varepsilon_{i1}^{k_{i1}} < -\beta'(x_{i1}^{3-k_{i1}} - x_{i1}^{k_{i1}}) - v_i'(x_{i1}^{3-k_{i1}} - x_{i1}^{k_{i1}}),\\ &\vdots\\ &\varepsilon_{iJ}^{3-k_{iJ}} - \varepsilon_{iJ}^{k_{iJ}} < -\beta'(x_{iJ}^{3-k_{iJ}} - x_{iJ}^{k_{iJ}}) - v_i'(x_{iJ}^{3-k_{iJ}} - x_{iJ}^{k_{1J}}) \Big| v_i'\Big]\phi(v_i)dv_i \qquad \text{(F-11)}\\ = \int_{-\infty}^{\infty}\prod_{j=1}^{J} P\Big[&\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}} < -\beta'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}}) - v_i'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{1j}}) \Big| v_i\Big]\phi(v_i)dv_i\\ = \int_{-\infty}^{\infty}\prod_{j=1}^{J} \Phi&\left[\left(\frac{\beta + v_i}{\sqrt{2\sigma_\varepsilon}}\right)'(x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}})\right]\phi(v_i)dv_i,\end{aligned}$$

where ϕ is the L-variate multinormal density function with mean vector 0 and covariance matrix Σ:

$$\phi(v_i) = \{2\pi|\Sigma|\}^{-\frac{L}{2}} \exp\left[-\frac{1}{2}v_i'\Sigma^{-1}v_i\right]. \qquad \text{(F-12)}$$

The order of magnitude of the integral in Equation F-11 is determined by the assumptions made for about Σ. Specifically, it is equal to the number of distinct nonzero diagonal elements, which is the number of parameters assumed to be random.[5] For the purpose of estimation by maximum likelihood, Equation F-11 can be evaluated in either of two ways. First, since the kernel of $\phi(\cdot)$ is of the form $\exp(-[\cdot])^2$, the combination of Equations F-11 and F-12 can be written as

$$\int_{-\infty}^{\infty} g(v)e^{-v^2}dv$$

(for the case of a single random parameter) so that Hermite polynomial quadrature of the integrals in Equation F-11 is fast enough to be a practical computational method (Waldman, 1985). The quadrature could be made as accurate as necessary for the convergence of an optimization algorithm, such as Maxlik in Gauss. If the order of magnitude of the integral is small, as is likely to be the case in the current application (in Hausman and Wise, 1978, three parameters are random), the estimation problem is computationally tractable by quadrature. Second, if quadrature is not feasible because the order of magnitude is too large, a simulation method could be used (see Layton and Brown, 1998; Train, 1998). The likelihood is simply

5. Under normality and the additional assumption of a diagonal Σ, the multinormal joint density of v_i, $\phi(v_i)$, factors into the product over k of $\phi(v_i)$ although no further simplification appears to be possible because of each element of v_i appears in each probability. This means that there is no computational advantage in this additional assumption.

$$L\left(k_{ij}, i=1,\ldots,n,\ j=1,\ldots,J \,\middle|\, x_{ij}^{1}, x_{ij}^{2}; \beta, \sigma_{\varepsilon}, \Sigma\right) = \prod_{i=1}^{n} P_i\ , \tag{F-13}$$

where the P_i are from Equation F-11.

F.4 EXTENDING THE MODEL TO INCLUDE THE STATUS QUO — CONSTANT PARAMETERS

After choosing k_{ij}, individuals answer a question stating whether alternative k_{ij} would be chosen over the status quo. The status quo (e.g., "doing nothing") essentially involves a choice alternative with all baseline attribute levels and zero cost. Let the status quo be indicated by 0. There are now four kinds of observations. Let the binary variable Z_{ij}^{1} indicate the choice of alternative 1 or 2 for individual *i* on occasion *j*, and let the binary variable Z_{ij}^{2} indicate the chosen alternative or the status quo. These are defined by:

$$Z_{ij}^{1} = \begin{cases} 0 \text{ choose } 1 \\ 1 \text{ choose } 2 \end{cases} \qquad Z_{ij}^{2} = \begin{cases} 0 \text{ choose } 1 \text{ or } 2 \text{ over status quo} \\ 1 \text{ choose status quo over } 1 \text{ or } 2 \end{cases}. \tag{F-14}$$

Note that there is an asymmetry here: when the status quo is chosen over 1 or 2 ($Z_{ij}^{2} = 1$), a complete ranking of the three alternatives has been determined; when 1 or 2 is chosen over the status quo ($Z_{ij}^{2} = 0$), all that is known is that 1 or 2 is the most preferred alternative.

Utility for the status quo, U_i^0, is given by equation 1 as:

$$U_i^0 = \beta' x^0 + \varepsilon_i^0\ , \tag{F-15}$$

where ε_i^0 are disturbances and x^0 are the characteristics of the current forecasting system.[6] Note that the characteristics of the status quo do not change (no subscripts on x^0), and that the utility of the status quo is evaluated once by each individual (U_i^0 and ε_i^0 are subscripted with *i* only). The following assumption characterizes the disturbances:

6 We first model the error term on the status quo identical to that on the A-B choice and then allow it to have a different variance as indicated here. These are called the common variance and independent variance approaches in Chapter 5 (see Table 5-3).

A3: The ε_i^0 are independent, identically distributed normal random variables with zero expectation and variance σ_0^2, assumed uncorrelated with $\varepsilon_{ij}^{k_{ij}}$.[7]

In the fixed coefficients model, for $Z_{ij}^2 = 0$, the probability of choosing alternative k_{ij} over alternative $3 - k_{ij}$ and then choosing alternative k_{ij} over the status quo is

$$\begin{aligned}
&P\left(U_{ij}^{k_{ij}} > U_{ij}^{3-k_{ij}}, U_{ij}^{k_{ij}} > U_i^0\right) \\
&= P\left(\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}} < -\beta'(\mathrm{x}_{ij}^{3-k_{ij}} - \mathrm{x}_{ij}^{k_{ij}}), \varepsilon_i^0 - \varepsilon_{ij}^{k_{ij}} < -\beta'(\mathrm{x}^0 - \mathrm{x}_{ij}^{k_{ij}})\right) \qquad \text{(F-16)} \\
&= \Phi_2\left[-\beta\left(\mathrm{x}_{ij}^{3-k_{ij}} - \mathrm{x}_{ij}^{k_{ij}}\right)\big/\sqrt{2}\sigma_\varepsilon, \beta'\left(\mathrm{x}^0 - \mathrm{x}_{ij}^{k_{ij}}\right)\big/\sqrt{\sigma_0^2 + \sigma_\varepsilon^2}; \rho\right],
\end{aligned}$$

where ρ is the correlation between $\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}}$ and $\varepsilon_i^0 - {}_{ij}^{k_{ij}}$,

$$\rho = \frac{\sigma_\varepsilon^2}{\sqrt{2\sigma_\varepsilon^2\left(\sigma_0^2 + \sigma_\varepsilon^2\right)}} = \frac{\sigma_\varepsilon}{\sqrt{2\left(\sigma_0^2 + \sigma_\varepsilon^2\right)}}, \qquad \text{(F-17)}$$

and Φ_2 is the standard bivariate normal distribution function. Similarly, $Z_{ij}^2 = 1$ for the probability of choosing alternative k_{ij} over alternative $3 - k_{ij}$ and then choosing the status quo over alternative k_{ij} is

$$\begin{aligned}
&P\left(U_{ij}^{k_{ij}} > U_{ij}^{3-k_{ij}}, U_{ij}^{k_{ij}} < U_i^0\right) \\
&= P\left(\varepsilon_{ij}^{3-k_{ij}} - \varepsilon_{ij}^{k_{ij}} < -\beta'(\mathrm{x}_{ij}^{3-k_{ij}} - \mathrm{x}_{ij}^{k_{ij}}), \varepsilon_i^0 - \varepsilon_{ij}^{k_{ij}} < -\beta'(\mathrm{x}^0 - \mathrm{x}_{ij}^{k_{ij}})\right) \qquad \text{(F-18)} \\
&= \Phi_2\left[-\beta(\mathrm{x}_{ij}^{3-k_{ij}} - \mathrm{x}_{ij}^{k_{ij}})\big/\sqrt{2}\sigma_\varepsilon, \beta'(\mathrm{x}^0 - \mathrm{x}_{ij}^{k_{ij}})\big/\sqrt{\sigma_0^2 + \sigma_\varepsilon^2}; -\rho\right]
\end{aligned}$$

where the symmetry of the normal distribution has been utilized.

Let $\sigma_{0\varepsilon} = \sqrt{\sigma_0^2 + \sigma_\varepsilon^2}$, $x_{ij}^{01} = \left(x_{ij}^0 - x_{ij}^1\right)$, $x_{ij}^{02} = \left(x_{ij}^0 - x_{ij}^2\right)$, and $x_{ij}^{21} = \left(x_{ij}^2 - x_{ij}^1\right)$. Substituting these definitions into Equations F-16 and F-18 yields 7:

7 The error in the utility function for the status quo is likely to have a smaller variance than when valuing hypothetical situations. When it comes to estimation, a natural (and testable) hypothesis is $\sigma_0^2 = \sigma_\varepsilon^2$.

$$
\begin{aligned}
&P\left(Z_{ij}^1 = 0,\, Z_{ij}^2 = 0\right) = \Phi_2\left[-\beta' x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon,\, -\beta' x_{ij}^{01} \big/ \sigma_{0\varepsilon};\, \rho\right] \\
&P\left(Z_{ij}^1 = 0,\, Z_{ij}^2 = 1\right) = \Phi_2\left[-\beta' x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon,\, \beta' x_{ij}^{01} \big/ \sigma_{0\varepsilon};\, -\rho\right] \\
&P\left(Z_{ij}^1 = 1,\, Z_{ij}^2 = 0\right) = \Phi_2\left[-\beta' x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon,\, -\beta' x_{ij}^{01} \big/ \sigma_{0\varepsilon};\, \rho\right] \\
&P\left(Z_{ij}^1 = 1,\, Z_{ij}^2 = 1\right) = \Phi_2\left[-\beta' x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon,\, \beta' x_{ij}^{01} \big/ \sigma_{0\varepsilon};\, -\rho\right].
\end{aligned}
\tag{F-19}
$$

Under assumptions A1 - A3, the unit of observation, as in the basic model, is an *i*, *j* pair, so that the likelihood is the product of these J_n probabilities:

$$
\begin{aligned}
&L\left(Z_{ij}^1, Z_{ij}^2, i = 1, \ldots, n,\ j = 1, \ldots, J \,\middle|\, x_{ij}^1, x_{ij}^2, x^0;\, \beta, \sigma_\varepsilon, \sigma_0\right) = \\
&\prod_{i=1}^{n} \prod_{j=1}^{J} P\left(Z_{ij}^1, Z_{ij}^2\right).
\end{aligned}
\tag{F-20}
$$

For the purpose of coding this can be written:

$$
\begin{aligned}
&L\left(Z_{ij}^1, Z_{ij}^2, i = 1, \ldots, n,\ j = 1, \ldots, J \,\middle|\, x_{ij}^1, x_{ij}^2, x^0;\, \beta, \sigma_\varepsilon, \sigma_0\right) = \\
&\prod_{i=1}^{n} \prod_{j=1}^{J} \Phi_2 \left\{(-1)^{1-Z_{ij}^1}\, \beta' x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon, \right. \\
&\left. (-1)^{1-Z_{ij}^2} \left[\left(1 - Z_{ij}^1\right)\beta' x_{ij}^{01} + Z_{ij}^1 \beta' x_{ij}^{02}\right] \big/ \sigma_{0\varepsilon};\, (-1)^{Z_{ij}2} \rho \right\}.
\end{aligned}
\tag{F-21}
$$

F.5 A-B-STATUS QUO WITH RANDOM PARAMETERS

The extension to random parameters is straightforward. The generalization of equations like F-16 and F-18 is, for example,

$$
P\left[\left(U_{i1}^{k_{i1}} > U_{i1}^{3-k_{i1}}, U_{i1}^{k_{i1}} > U_i^0\right), \ldots, \left(U_{iJ}^{k_{iJ}} > U_{iJ}^{3-k_{iJ}}, U_{iJ}^{k_{iJ}} > U_i^0\right)\right]
\tag{F-22}
$$

(see Equation F-8). The likelihood becomes

$$
\begin{aligned}
&L\left(Z_{ij}^1, Z_{ij}^2, i = 1, \ldots, n,\ j = 1, \ldots, J \,\middle|\, x_{ij}^1, x_{ij}^2, x^0;\, \beta, \sigma_\varepsilon, \sigma_0, \sigma_v\right) = \\
&= \int_{-\infty}^{\infty} \prod_{j=1}^{J} \Phi_2 \left\{(-1)^{1-Z_{ij}^1} \left(\beta' + v_i\right) x_{ij}^{21} \big/ \sqrt{2}\sigma_\varepsilon, \right. \\
&\left. (-1)^{1-Z_{ij}^2} \left[\left(1 - Z_{ij}^1\right)\left(\beta' + v_i\right) x_{ij}^{01} + Z_{ij}^1 \left(\beta' + v_i\right) x_{ij}^{02}\right] \big/ \sigma_{0\varepsilon};\, (-1)^{Z_{ij}^2} \rho \right\} \phi\left(v_i\right) dv_i.
\end{aligned}
\tag{F-23}
$$

F.6 WILLINGNESS-TO-PAY DATA: CONSTANT PARAMETERS

In addition to the SC data, a single scenario improving on the status quo is posed to respondents and their willingness to pay (WTP) for that scenario is elicited. Let x_i^* be the characteristics of the scenario, with disturbance ε_i^*. In the fixed-coefficient model, utility for this scenario is given by Equation F-1:

$$U_i^* = \beta' x_i^* + \varepsilon_i^*, \tag{F-24}$$

where ε_i^* is the disturbance in the evaluation of utility for the posed scenario. It is assumed that this error has the same distribution as ε_{ij}^1 and ε_{ij}^2, as it is an error in the valuation of utility for a hypothetical situation. The model for this SV data follows the usual algebraic derivation from Equation F-1, resulting in

$$WTP_i^* = \frac{1}{\beta_y}\left[\beta_{freq}(fr_i^* - fr^0) + \ldots + (\varepsilon_i^* - \varepsilon_i^0)\right], \tag{F-25}$$

where fr_i^* is the value of the frequency of forecasts in the hypothetical scenario, fr^0 is the frequency of forecasts in the status quo (three times daily), and β_y is the coefficient of income in the conditional indirect utility function. Then it follows that

$$WTP_i^* \sim N\left[\frac{\beta_{freq}}{\beta_y}\left(fr_i^* - fr^0\right) + \ldots, \frac{\sigma_\varepsilon^2 + \sigma_0^2}{\beta_y^2}\right]. \tag{F-26}$$

The log-likelihood of the *WTP* data is

$$-\frac{n}{2}\ln 2\pi - \frac{n}{2}\ln \sigma_\varepsilon^2 - \frac{1}{2\sigma_{0\varepsilon}^2}\sum_{i=1}^{n}\left[WTP_i - \frac{\beta_{freq}}{\beta_y}(fr_i^* - fr^0) + \ldots\right]^2. \tag{F-27}$$

The joint log-likelihood for the SC and SV data is the sum of the contributions from the two data sources (Equations F-19 and F-27). This is a limited information approach, as the correlation between WTP_i^* and the Z_{ij} is ignored.

F.7 WILLINGNESS-TO-PAY DATA: RANDOM PARAMETERS

In the random parameters model, conditional on ν_i the distribution of WTP_i^* is

$$WTP_i^* \Big| \nu_i \sim N\left[\frac{(\beta_{freq} + \nu_i^{fr})}{\beta_y}(fr_i^* - fr^0) + \ \ldots, \frac{\sigma_\varepsilon^2 + \sigma_0^2}{\beta_y^2}\right], \tag{F-28}$$

where, for example, ν_i^{fr} is the component of ν_i corresponding to frequency of forecasts. The increment to the SV portion of the likelihood is then found by integration:

$$f\left(WTP_i^*\right) = \int_{-\infty}^{\infty} f\left(WTP_i^* \middle| \nu_i\right)\phi(\nu_i)d\nu_i, \tag{F-29}$$

where $\phi(\nu_i)$ is given in Equation F-12.

Note that there are no new parameters in the likelihood as a result of the SV data. The existence of the *WTP* data is a source of additional information on the parameters of Equation F-1. If respondents behave in their selection of *WTP* in the same way as in their choice selection, estimation of the basic model parameters should be more precise. The likelihood can be weighted to accommodate different degrees of confidence in the two types of data. Finally, the cardinality of WTP_i^* means that now σ_ε and σ_0 are identified.

In the fixed parameter model WTP_i^* and the Z_{ij} are correlated because they are functions of the common disturbance ε_i^0. In the random parameter model the WTP_i^* and Z_{ij}^1 and Z_{ij}^2 are correlated because they are functions of both the common disturbance ε_i^0 and the parameter error ν_i. A full-information approach maximizes the joint likelihood, over *i*, of

$$\left(Z_i^1, Z_i^2, WTP_i^*\right). \tag{F-30}$$

This is a mix of discrete and continuous variables. A function that expresses the joint probability of Z_i^1, Z_i^2 and density WTP_i^* is

$$P\left(Z_i^1, Z_i^2 \middle| WTP_i^*\right) f\left(WTP_i^*\right), \tag{F-31}$$

where $f\left(WTP_i^*\right)$ is given by Equation F-29. Equivalently, the joint probability of Z_i^1, Z_i^2 and density WTP_i^* can be expressed by

$$f\left(WTP_i^* \middle| Z_i^1, Z_i^2\right) P\left(Z_i^1, Z_i^2\right), \tag{F-32}$$

where $P\left(Z_i^1, Z_i^2\right)$ is given by Equation F-19 (see Amemiya, 1994, pps. 57-59). Expressions for $P\left(Z_i^1, Z_i^2 \middle| WTP_i^*\right)$ and $f\left(WTP_i^* \middle| Z_i^1, Z_i^2\right)$ are subjects of future research.

F.8 EMPIRICAL RESULTS

Table F-1 presents parameter estimates for the random coefficient model of Section F.5 where one parameter is assumed to be random. Each parameter in the model was allowed to be random, represented by successive columns of the table. The estimated standard deviation of the random component, the mean log-likelihood, and the chi-squared test of the null hypothesis of nonrandom parameters are reported in the last three rows.

Table F-1
A-B-Status Quo — Random Parameter Model

Random Parameter	None	Frequency	One Day	Multiday	Detail	Cost
Variable						
Frequency	-0.043	-0.047	0.033	-0.084	-0.065	-0.063
One-day forecast	612	0.667	0.736	0.686	0.646	0.688
Multiday forecast	0.476	0.476	0.503	0.611	0.506	0.537
Geographic detail	-0.097	-0.096	-0.119	-0.116	-0.127	-0.107
Cost	-0.591	-0.651	-0.717	-0.703	-0.657	-0.707
$\hat{\sigma}_v$		1.190	0.741	1.440	0.209	0.632
Mean log-L	-0.9967	-0.9861	-0.9613	-0.9696	-0.9859	-0.9763
$\chi^2_{(1)}$ test		14.24	47.58	36.42	14.51	27.42

Note: All parameter estimates are statistically significant at conventional levels (asymptotic t-statistics between 3 and 8), except for frequency, which is never significant.

Table F-2 presents parameter estimates for the constant coefficient model of Section F.5 where we've interacted different variables with cost to explore issues of heterogeneity. The no-interaction model is reported first. In the "education" model, cost is found to be less important (higher WTP) for more educated respondents. The marginal utility of income is now [-0.153 + (0.004 * Years of Education)] and so it is less negative for higher education individuals. A smaller marginal utility of income leads to higher WTP estimates.

Table F-2
A-B-Nothing Independent Variance Probit Model
(standard errors in parenthesis)

Interaction Variable	None	Educ	Gender	Accept
Frequency	-0.046 (0.005)	-0.047 (0.005)	-0.046 (0.005)	-0.050 (0.005)
One-day	0.062 (0.004)	0.062 (0.004)	0.062 (0.004)	0.051 (0.003)
Multiday	0.032 (0.005)	0.032 (0.005)	0.033 (0.005)	0.023 (0.004)
Geographic detail	-0.008 (0.002)	-0.008 (0.002)	-0.008 (0.002)	-0.005 (0.001)
Cost	-0.087 (0.005)	-0.153 (0.021)	-0.088 (0.005)	-0.072 (0.004)
Cost X educ	-	0.004 (0.001)	-	-
Cost X gender	-	-	0.005 (0.003)	-
Cost X accept	-	-	-	0.062 (0.004)
Log lamb	0.907 (0.099)	0.894 (0.097)	0.934 (0.103)	0.307 (0.058)
Implied ratio of disturbances, sig02/sige2 =	11.257	not calculated	11.944	2.696

All parameter estimates are significant at less than one percent except the Cost x Gender interaction which is significant at less than 5%.

From the "cost model," cost is 10% more important to men. The marginal utility of income for men is -0.0933 (-0.0884 - 0.0049) compared to women's -0.0835 (-0.0884 + 0.0049). Again, the smaller (in absolute terms) value of the marginal utility of income for women implied higher WTP values for women for the same weather forecast improvement program compared to men.

Finally we examined the impact of the scenario acceptance factor score on the marginal utility of income measure. The highly significant interaction term between accept and cost implies that WTP will be much greater for individuals with higher ACCEPT scores: coefficient of cost = -.0724 + .062*ACCEPT. As the ACCEPT factor scores ranged from -1.784 to 1.772, the range of marginal utility of income -0.183 to 0.038, so since this includes zero, implying a potentially infinite WTP for those with largest ACCEPT.

Hermite Polynomial Quadrature

Hermite polynomial quadrature is a method of approximating integrals of functions on $(-\infty, \infty)$ based on standard Gaussian methods (Butler and Moffit, 1982; Waldman, 1985). The equation is

$$\int_{-\infty}^{\infty} e^{-v^2} f(v) dv = \sum_{m=1}^{M} w_m f(v_m) + R_m , \tag{F-33}$$

where $f(v)$ is that part of the integrand in Equation F-27 with e^{-v^2} factored out. Let $\Delta x_{ij} = x_{ij}^{3-k_{ij}} - x_{ij}^{k_{ij}}$ and indicate the elements of this vector with superscripts. Suppose without loss of generality the single varying parameter is the first. Then $f(v)$ is:

$$f(v) = \pi^{-1/2} \prod_{j=1}^{J} \Phi\left[(2\sigma_\varepsilon^2)^{-1/2}(-\beta' \Delta x_{ij} - \sqrt{2}\sigma_v v \Delta x_{ij}^1)\right]. \tag{F-34}$$

Note the necessary change of variable to accommodate the fact that the normal kernel is $e^{-\frac{1}{2}v^2}$ and not e^{-v^2}. Here v_i is the ith zero of the Hermite polynomial $H_m(v)$, m is the number of evaluation points, and w_i are the weights, given by:

$$w_i = \frac{2^{m-1} m! \sqrt{\pi}}{m^2 [H_{m-1}(v_i)]^2} . \tag{F-35}$$

The remainder is:

$$R_m = \frac{m! \sqrt{\pi}}{2^m (2m)!} f^{(2m)}(\xi), \quad 0 < \xi < \infty . \tag{F-36}$$

For the case of two (or more) varying parameters, the elements in the random vector v_i in Equations F-27 and F-12 are treated separately and the numerical integration is done from the inside out. Without loss of generality, suppose the two varying parameters are the first and the second. Then Equation F-27 becomes:

$$\begin{aligned} P_i = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \prod_{j=1}^{J} \Phi\left[-(2\sigma_\varepsilon^2)^{-1/2}(\beta' \Delta x_{ij} + v_1 \Delta x_{ij}^1 + v_2 \Delta x_{ij}^2)\right] \\ \frac{1}{2\pi\sigma_{v_1}\sigma_{v_2}} \exp\left(-\frac{v_1^2}{2\sigma_{v_1}^2} - \frac{v_2^2}{2\sigma_{v_2}^2}\right) dv_2 dv_1 , \end{aligned} \tag{F-37}$$

under the assumption that v_1 and v_2 are uncorrelated. This can be rewritten

$$P_i = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \prod_{j=1}^{J} \left(2\sigma_\varepsilon^2\right)^{-1/2} \Phi\left(-\beta'\Delta \mathrm{x}_{ij} - v_1 \Delta x_{ij}^1 - v_2 \Delta x_{ij}^2\right) \right.$$
$$\left. \frac{1}{2\pi\sigma_{v_2}} \exp(-\frac{v_2^2}{2\sigma_{v2}^2}) dv_2 \right] \frac{1}{\sqrt{2\pi}\sigma_{v_1}} \exp(-\frac{-v_1^2}{2\sigma_{v_1}^2}) dv_1 \,. \quad \text{(F-38)}$$

The integral inside the brackets is similar to the single varying parameter case, and can be evaluated in that manner. Call this quantity $g(v_1)$. It is a function of $\beta, \sigma_{v_1}, \sigma_{v_2}$, and v_1, but not a function of v_2 (recall σ_ε is not identified in this model). Equation F-38 may be written

$$P_i = \int_{-\infty}^{\infty} g\left(v_1\right) \frac{1}{\sqrt{2}\sigma_{v_1}} \exp(-\frac{v_1^2}{2\sigma_{v_1}^2}) dv_1 \,, \quad \text{(F-39)}$$

which again can be evaluated as a single quadrature. The number of function evaluations increases exponentially. That is, if five function evaluations are needed when there is a single varying parameter, 25 are needed for two, 125 for three, etc.

The following table, from Abramowitz and Stegun (1964), gives v_i, w_i for various m:

$\pm V_I$	$(10^J)\ W_I$
$M = 2$	
0.70710 67811 86548	(-1) 8.86226 92545 28
$M = 3$	
0.0	(0) 1.18163 59006 04
1.22474 48713 91589	(-1) 2.95408 97515 09
$M = 4$	
0.52464 76232 85290	(-1) 8.04914 09000 55
1.65058 01238 85758	(-2) 8.13128 35477 25
$M = 5$	
0.0	(-1) 9.45308 72048 29
0.95875 24646 13819	(-1) 3.93619 32315 22
2.02018 28704 56086	(-2) 1.99532 42059 05

APPENDIX G
DATA ADJUSTMENTS AND SUMMARY STATISTICS

Data Quality and Sample Characteristics

For data analysis we deleted the five Boulder pretest subjects from the in-house pretest (two of these were "attendees" who completed the survey). The purpose of the Boulder pretest was to estimate the time necessary to complete the survey and to test the implementation materials. Since the implementation format was slightly different than the other cities, it was deemed best to exclude these two from further analysis.

Despite efforts to ensure that all individuals answered all questions, there were some nonresponses to individual questions. In examining item nonresponse, we looked at only the "attendees." Overall item nonresponse was 0.68%. The highest item nonresponse was for Question 11, which asked individuals their feeling about the "adequacy of geographic detail to 30 miles by 30 miles." Thirteen of 381 respondents did not answer this question, for an item nonresponse rate of 3.41%. Overall, 20% of all item nonresponses were in the various categories for Question 37, one of the WTP follow-up questions, suggesting that some individuals did not understand the skip pattern in Question 35 and thus skipped past Question 37.

To examine missing age responses, we replaced missing values for sociodemographics with mean values from the balance of the data set for ethnicity, Spanish heritage, education category, income, and gender. Using these data we developed a regression model for age to fit age for individuals with missing age values or codes. Age was fitted in this manner for 5 of the 673 recruited individuals.

There is an 87% correlation between income categories as reported in the telephone screener and the income reported in the survey instrument. The telephone screener had 37 refusals to provide income information, whereas with the written instrument only one person did not answer the question. This result, along with the fact that the written instrument had more categories for income (and thus obtained more detail), led us to rely on income as reported in the written instrument for data analysis. For one individual with a missing income response from both the written survey and the telephone recruitment, we set income equal to the median (for this individual income was set to $50,000). The median was used rather than the mean since income distributions are generally left truncated and right skewed and thus median values are potentially more representative of the "typical" individual in the population. Income and educational attainment were converted from categorical responses in the survey instrument to continuous variables used for statistical analysis shown below.

In creating the gender variable we compared responses to the telephone screener coding of gender to the individual's written responses from the in person survey. Assuming that the written responses by the individual are correct, 12 out of 380 (or about 3.2% of the telephone interviewer codings) were incorrect. The gender variable (coded as -1 for male and +1 for female) is thus based on the individuals' response to Question H2 in the in-person survey.

For Question 3 regarding how often individuals used different sources to obtain weather forecast information, if individuals responded that they don't know, we coded their response as "never."

For Question 14 if individuals did not respond to this question, we recoded this as a “no” response for that expenditure category.

There are 18 potential choice question responses in the survey (two each for nine choice questions). For the 383 respondents, this makes a total of 6,894 potential choice question responses. There are 64 missing responses (or slightly less than 1% item nonresponse over the nine choice questions). Only three of these 64 missing responses are for the A-B portion of the question, the balance (61 item nonresponses) are for the follow-up question. We randomly coded the missing responses to the missing three primary (A-B) responses in order to retain the balance of those individuals’ responses to the other choice questions in the choice analysis. As a conservative approach to preserving the existing data, we coded the 61 missing responses to the follow-up question as a “1” meaning the individual would prefer no change to the status quo. This thus leads to an understatement of values for weather forecast improvements.

For purposes of data analysis and to not lose observations we set missing values of any other equal to the mean of the other responses (excluding don’t know responses) unless indicated otherwise in this discussion. We made these adjustment only for the primary section of the survey (not the severe weather section). Table G-1 presents summary statistics for variables from the 381 respondents following the adjustments described above. Table G-2 presents means and standard deviations for these variables by city.

Table G-1
Summary Statistics
All Cities Combined

Variable	Label	N	Mean	Std Dev	Min	Max
VERSION	Version	381	10.454	5.751	1	20
CITY	Session location	381	4.94	2.546	1	9
B4	Age	369	43.488	14.754	18	84
B4A	Age category	8	3.125	0.641	2	4
B5_1	Race	377	1.369	0.911	1	5
B5_2	Race	3	3.333	1.155	2	4
B6	Hispanic descent	381	1.905	0.293	1	2
B7	Level of education	381	3.439	1.051	1	6
B8	Household income	343	4.848	2.649	1	10
B9	Gender	381	1.574	0.495	1	2
Q1	Heard of NWS before today	381	1.105	0.307	1	2
Q2A	Importance: Chance of rain, snow, or hail	381	4.302	0.821	1	5
Q2B	Importance: Amount of rain, snow, or hail	381	4.018	0.958	1	5
Q2C	Importance: How cloudy it will be	381	2.741	1.082	1	5
Q2D	Importance: Low temperature	381	3.741	1.057	1	5
Q2E	Importance: High temperature	381	3.847	1.007	1	5
Q2F	Importance: How windy it will be	381	3.282	1.082	1	5
Q2G	Importance: Air pressure	381	2.208	1.129	1	5
Q3A	Forecast source: Local TV newscasts	381	4.047	1.151	1	6

Table G-1
Summary Statistics
All Cities Combined (cont.)

Variable	Label	N	Mean	Std Dev	Min	Max
Q3B	Forecast source: Cable TV stations	381	2.656	1.499	1	6
Q3C	Forecast source: Newspaper	381	2.228	1.202	1	5
Q3D	Forecast source: Commercial or public radio	381	3.213	1.518	1	6
Q3E	Forecast source: NOAA Weather radio	381	1.205	0.707	1	6
Q3F	Forecast source: Internet	381	1.824	1.169	1	6
Q3G	Forecast source: Other people	381	2.451	1.244	1	6
Q4A	Forecast use: Dress for the day	381	3.966	1.132	1	5
Q4B	Forecast use: How to get to work/school/store	381	2.877	1.313	1	5
Q4C	Forecast use: Job or business	381	2.761	1.41	1	5
Q4D	Forecast use: House or yardwork	381	3.105	1.235	1	5
Q4E	Forecast use: Social activities	381	3.207	1.131	1	5
Q4F	Forecast use: Vacation or travel	381	3.607	1.193	1	5
Q4G	Forecast use: Planning for the weekend	381	3.759	1.112	1	5
Q5	Updates 4 times a day	381	3.301	0.684	1	5
Q6A	Updates 6 times a day	381	2.611	0.989	1	5
Q6B	Updates 9 times a day	381	2.08	1.041	1	5
Q6C	Updates 12 times a day	381	1.96	1.234	1	5
Q7	Adequacy of 80% correctness of forecasts	381	2.878	0.815	1	5
Q8A	Usefulness of 85% correctness	381	3.048	0.978	1	5
Q8B	Usefulness of 90% correctness	381	3.404	1.044	1	5
Q8C	Usefulness of 95% correctness	381	3.812	1.216	1	5
Q9	Adequacy of weather forecasts 5 days in advance	381	2.888	0.845	1	5
Q10A	Usefulness of 7-day forecast as accurate as 5-day	381	3.291	0.982	1	5
Q10B	Usefulness of 10-day forecast as accurate as 5-day	381	3.295	1.123	1	5
Q10C	Usefulness of 14-day forecast as accurate as 5-day	381	3.354	1.343	1	5
Q11	Adequacy of geography detail to 30 miles by 30 miles	381	2.742	0.88	1	5
Q12A	Usefulness of detail 15 miles by 15 miles	381	3.076	0.996	1	5
Q12B	Usefulness of detail 7 miles by 7 miles	381	3.142	1.105	1	5
Q12C	Usefulness of detail 3 miles by 3 miles	381	3.211	1.402	1	5
Q13	Spending for the NWS for weather forecasting	381	2.274	0.556	1	3
Q14A	Reduce spending: Food	381	1.927	0.261	1	2
Q14B	Reduce spending: Housing	381	1.961	0.195	1	2
Q14C	Reduce spending: Clothing and services	381	1.745	0.436	1	2
Q14D	Reduce spending: Transportation	381	1.858	0.349	1	2
Q14E	Reduce spending: Health care	381	1.94	0.238	1	2
Q14F	Reduce spending: Entertainment	381	1.433	0.496	1	2
Q14G	Reduce spending: Savings or investments	381	1.761	0.427	1	2
Q14H	Reduce spending: other expenditures	378	1.833	0.373	1	2
Q34A	Cannot afford more	381	2.461	1.413	1	5
Q34B	Should not have to pay	381	2.163	1.386	1	5
Q34C	Useful to have improved weather forecasting	381	3.14	1.321	1	5
Q34D	Important to improve weather forecasting	381	2.931	1.401	1	5

Table G-1
Summary Statistics
All Cities Combined (cont.)

Variable	Label	N	Mean	Std Dev	Min	Max
Q34E	Program will not work or will not happen	381	1.658	1.126	1	5
Q34F	My responsibility to pay for improvement	381	2.003	1.195	1	5
Q34G	Private sector should take over weather forecasting	381	1.577	1.077	1	5
Q34H	Do not use weather forecasts	381	1.75	1.176	1	5
Q34I	Money would not be used for program	381	1.636	1.121	1	5
Q34J	Need more information	381	2.358	1.428	1	5
Q34K	Current weather forecasts are good enough	381	2.589	1.46	1	5
Q35	$ willing to spend on weather forecasting improvement	332	1.898	0.763	1	4
Q36	% for improving forecasting under normal conditions	273	45.018	32.28	0	100
Q37A	Importance: Frequency of updated forecasts	381	2.527	1.253	1	5
Q37B	Importance: Accuracy of one-day forecasts	381	3.806	1.147	1	5
Q37C	Importance: Accuracy of multiday forecasts	381	3.714	1.133	1	5
Q37D	Importance: Geographic detail	381	3.272	1.264	1	5
Q37E	Importance: Yearly cost to household	381	3.639	1.267	1	5
Q38	Confidence in decision for choosing program	381	3.871	0.892	1	5
Q39	Represent what respondent would like NWS to do	381	3.654	0.943	1	5
H1	Years lived in current area	381	19.814	17.08	0	84
H2	Gender	381	1.433	0.496	1	2
H3	Number of people in household	381	2.732	1.56	1	11
H4_1	Employed full-time	381	0.512	0.501	0	1
H4_2	Employed part-time	381	0.181	0.386	0	1
H4_3	Retired	381	0.144	0.352	0	1
H4_4	Homemaker	381	0.094	0.293	0	1
H4_5	Student	381	0.115	0.32	0	1
H4_6	Unemployed	381	0.087	0.282	0	1
H5	Average percent of on-the-job time spent outdoors	381	19.197	26.531	0	100
H6	Average number of hours per week traveling outside	381	12.843	29.563	0	520
H7	Average percent of leisure time spent outdoors	381	46.039	20.256	10	100
H8	Average hours per week spent working outside	381	9.696	13.414	0	150
H9	Total household income (before taxes) in 2000	380	5.366	3.156	1	14
O1	Import. of weather forecasts for all weather	379	4.161	0.93	1	5
O3A	Thunderstorms	381	3.976	1.15	1	5
O3B	Extreme heat	381	3.924	1.134	1	5
O3C	Extreme cold	378	4.153	1.18	1	5
O3D	Fog or low clouds	378	3.119	1.207	1	5
O3E	Lightning	377	3.69	1.17	1	5
O3F	Hurricanes	360	2.992	1.798	1	5
O3G	Tornadoes	368	4.261	1.299	1	5
O3H	Wind storms	371	3.989	1.155	1	5
O3I	Fire danger/drought	372	3.667	1.349	1	5
O3J	Flash floods	366	3.642	1.387	1	5
O3K	Snow or ice storms	371	4.178	1.334	1	5

Table G-1
Summary Statistics
All Cities Combined (cont.)

Variable	Label	N	Mean	Std Dev	Min	Max
O3L	Hail	371	3.933	1.245	1	5
O3M	Air quality	374	3.433	1.283	1	5
O3N	Other	53	3.623	1.62	1	5
O4A	Watches and warnings: Thunderstorms	371	3.973	0.735	1	5
O4B	Watches and warnings: Extreme heat	371	4.221	0.742	1	5
O4C	Watches and warnings: Extreme cold	362	4.185	0.843	1	5
O4D	Watches and warnings: Fog or low clouds	334	3.659	0.844	1	5
O4E	Watches and warnings: Lightning	344	3.753	0.864	1	5
O4F	Watches and warnings: Hurricanes	246	3.736	1.29	1	5
O4G	Watches and warnings: Tornadoes	328	3.82	0.977	1	5
O4H	Watches and warnings: Wind storms	336	3.792	0.893	1	5
O4I	Watches and warnings: Fire danger/drought	328	3.936	0.884	1	5
O4J	Watches and warnings: Flash floods	316	3.671	0.982	1	5
O4K	Watches and warnings: Snow or ice storms	341	3.845	0.915	1	5
O4L	Watches and warnings: Hail	339	3.552	0.967	1	5
O4M	Watches and warnings: Air quality	294	3.67	0.972	1	5
O4N	Watches and warnings: Other	42	3.738	1.014	1	5
O5A	One condition requiring more effort	372	6.142	6.496	1	34
O5B	One condition requiring more effort	143	5.93	5.448	1	33
O5C	One condition requiring more effort	24	5.75	4.465	2	21
O5D	One condition requiring more effort	7	8.429	5.442	2	17
O5E	One condition requiring more effort	2	8	1.414	7	9

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
n	**40**	**46**	**48**	**43**	**40**	**44**	**42**	**39**	**39**
VERSION	10.875 (5.712)	11.109 (5.740)	9.875 (6.066)	10.349 (6.039)	10.500 (5.311)	9.682 (5.472)	9.810 (5.956)	11.205 (6.416)	10.846 (5.204)
CITY	2.000 (0.000)	4.000 (0.000)	6.000 (0.000)	1.000 (0.000)	9.000 (0.000)	3.000 (0.000)	5.000 (0.000)	7.000 (0.000)	8.000 (0.000)
B4	45.359 (16.750)	44.795 (14.313)	47.318 (16.179)	48.023 (13.655)	39.650 (13.433)	40.927 (14.006)	42.488 (14.271)	41.974 (14.547)	39.921 (14.010)
B5_1	1.150 (0.483)	1.174 (0.677)	1.146 (0.412)	1.571 (1.252)	1.795 (1.196)	1.326 (0.778)	1.341 (0.762)	1.282 (0.857)	1.615 (1.269)
B6	2.000 (0.000)	1.978 (0.147)	1.958 (0.202)	1.884 (0.324)	1.672 (0.473)	1.975 (0.151)	1.950 (0.216)	1.923 (0.270)	1.769 (0.427)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
B7	3.450 (1.197)	3.348 (0.766)	3.708 (1.091)	3.721 (1.054)	3.200 (1.091)	3.636 (1.080)	3.079 (1.198)	3.308 (0.922)	3.436 (0.882)
B8	5.579 (2.956)	4.220 (2.475)	5.463 (2.675)	5.475 (2.727)	4.765 (2.349)	4.756 (2.547)	4.429 (2.704)	3.917 (2.285)	4.919 (2.773)
B9	1.600 (0.496)	1.696 (0.465)	1.646 (0.483)	1.512 (0.506)	1.550 (0.504)	1.545 (0.504)	1.584 (0.493)	1.590 (0.498)	1.410 (0.498)
Q1	1.075 (0.267)	1.065 (0.250)	1.021 (0.144)	1.116 (0.324)	1.278 (0.451)	1.068 (0.255)	1.095 (0.297)	1.103 (0.307)	1.154 (0.366)
Q2A	4.600 (0.591)	4.413 (0.580)	4.354 (0.758)	4.326 (0.644)	4.175 (0.813)	4.477 (0.590)	4.286 (0.835)	4.103 (1.119)	3.923 (1.178)
Q2B	4.375 (0.806)	3.957 (0.815)	4.000 (0.851)	4.163 (0.814)	4.025 (1.165)	4.045 (0.888)	4.262 (0.857)	3.744 (1.163)	3.564 (1.071)
Q2C	2.969 (1.000)	2.630 (1.019)	2.417 (0.964)	2.953 (1.133)	2.719 (1.011)	2.818 (1.018)	2.690 (1.137)	2.641 (1.158)	2.897 (1.273)
Q2D	3.719 (1.011)	3.734 (0.904)	4.021 (1.062)	3.791 (0.914)	3.725 (1.062)	3.750 (1.037)	3.952 (0.987)	3.590 (1.141)	3.308 (1.321)
Q2E	3.746 (1.031)	3.717 (0.911)	4.104 (0.994)	3.977 (0.859)	3.875 (1.067)	3.864 (0.824)	3.929 (0.997)	3.744 (1.141)	3.615 (1.227)
Q2F	3.257 (1.031)	3.478 (0.863)	3.083 (1.127)	3.279 (1.031)	3.375 (1.125)	3.256 (1.102)	3.714 (1.111)	3.051 (1.123)	3.026 (1.135)
Q2G	2.330 (0.996)	1.957 (0.893)	1.958 (1.051)	2.349 (1.270)	2.550 (1.280)	2.136 (1.025)	2.429 (1.252)	2.051 (1.146)	2.179 (1.167)
Q3A	4.400 (1.236)	4.196 (0.885)	4.271 (1.005)	4.186 (0.852)	4.025 (1.310)	3.614 (1.224)	4.024 (1.158)	3.974 (1.308)	3.692 (1.217)
Q3B	2.925 (1.655)	2.630 (1.420)	2.688 (1.532)	2.256 (1.364)	2.975 (1.405)	2.659 (1.642)	2.786 (1.474)	2.385 (1.515)	2.615 (1.462)
Q3C	2.175 (1.238)	2.348 (1.233)	2.688 (1.206)	2.326 (1.190)	1.775 (1.230)	2.545 (1.088)	1.690 (0.975)	2.256 (1.186)	2.128 (1.196)
Q3D	3.650 (1.733)	2.957 (1.577)	3.438 (1.253)	3.372 (1.589)	2.900 (1.516)	3.636 (1.526)	2.857 (1.424)	3.308 (1.195)	2.744 (1.618)
Q3E	1.100 (0.379)	1.152 (0.666)	1.458 (1.110)	1.256 (0.790)	1.375 (1.030)	1.205 (0.509)	1.095 (0.297)	1.128 (0.656)	1.026 (0.160)
Q3F	2.125 (1.305)	1.500 (0.960)	1.750 (1.062)	1.930 (1.421)	1.650 (1.001)	2.159 (1.293)	1.571 (1.151)	1.769 (1.063)	2.000 (1.100)
Q3G	2.525 (1.358)	2.478 (1.130)	2.479 (1.111)	2.442 (1.368)	2.525 (1.601)	2.341 (1.055)	2.595 (1.231)	2.410 (1.186)	2.256 (1.208)
Q4A	4.200 (0.823)	4.348 (0.971)	4.063 (1.174)	4.186 (0.880)	3.475 (1.240)	4.273 (0.899)	4.095 (1.008)	3.821 (1.254)	3.077 (1.326)
Q4B	3.150 (1.562)	2.500 (1.225)	2.708 (1.184)	3.023 (1.165)	3.075 (1.457)	3.227 (1.198)	3.000 (1.361)	2.872 (1.239)	2.359 (1.267)
Q4C	2.975 (1.609)	2.674 (1.317)	2.250 (1.120)	2.930 (1.352)	2.869 (1.488)	2.955 (1.363)	3.167 (1.560)	2.667 (1.344)	2.410 (1.409)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
Q4D	3.250 (1.171)	3.217 (1.114)	3.438 (1.050)	3.070 (1.055)	3.075 (1.492)	3.023 (1.267)	3.143 (1.201)	3.000 (1.338)	2.644 (1.387)
Q4E	3.130 (1.017)	3.087 (1.151)	3.333 (0.996)	3.279 (0.984)	3.605 (1.234)	3.341 (1.200)	3.119 (1.173)	3.051 (1.099)	2.882 (1.262)
Q4F	3.475 (1.219)	3.644 (1.057)	3.458 (1.220)	3.535 (1.222)	4.165 (1.110)	3.477 (1.248)	3.667 (1.119)	3.590 (1.229)	3.487 (1.254)
Q4G	3.925 (0.829)	3.696 (1.171)	3.729 (1.125)	3.744 (0.978)	4.250 (1.006)	3.727 (1.086)	3.881 (1.087)	3.692 (1.260)	3.179 (1.233)
Q5	3.475 (0.716)	3.222 (0.651)	3.360 (0.599)	3.333 (0.807)	3.400 (0.591)	3.136 (0.594)	3.252 (0.615)	3.144 (0.767)	3.400 (0.777)
Q6A	2.475 (1.062)	2.739 (0.855)	2.525 (0.893)	2.814 (1.075)	2.765 (1.025)	2.500 (0.902)	2.929 (0.947)	2.410 (1.019)	2.308 (1.055)
Q6B	1.977 (0.947)	1.957 (0.965)	1.878 (0.891)	2.397 (1.311)	2.379 (1.124)	1.932 (0.925)	2.311 (1.023)	1.974 (0.932)	1.949 (1.123)
Q6C	1.924 (1.118)	1.717 (1.109)	1.749 (1.101)	2.208 (1.440)	2.374 (1.480)	1.750 (1.081)	2.213 (1.180)	1.974 (1.267)	1.795 (1.218)
Q7	3.100 (0.632)	2.910 (0.865)	2.914 (0.767)	2.907 (0.947)	2.975 (0.920)	2.727 (0.727)	2.759 (0.691)	2.660 (0.836)	2.949 (0.887)
Q8A	3.025 (1.000)	3.174 (0.950)	3.064 (0.885)	3.186 (1.006)	3.150 (1.122)	2.955 (0.806)	3.311 (0.949)	2.718 (1.050)	2.795 (0.978)
Q8B	3.450 (0.932)	3.500 (1.090)	3.413 (0.980)	3.349 (0.973)	3.520 (1.104)	3.341 (0.939)	3.629 (1.031)	3.231 (1.180)	3.179 (1.189)
Q8C	3.875 (1.159)	3.783 (1.209)	3.788 (1.090)	3.744 (1.236)	3.966 (1.271)	3.864 (1.069)	4.048 (1.147)	3.897 (1.231)	3.333 (1.510)
Q9	2.975 (0.698)	2.585 (0.831)	3.125 (0.841)	3.047 (0.975)	3.050 (0.846)	2.591 (0.726)	2.831 (0.881)	2.818 (0.823)	2.994 (0.828)
Q10A	3.200 (0.939)	3.348 (0.795)	3.208 (0.988)	3.442 (0.983)	3.375 (1.079)	3.295 (0.930)	3.452 (1.017)	3.103 (1.095)	3.179 (1.048)
Q10B	2.950 (1.108)	3.435 (1.025)	3.313 (1.133)	3.581 (0.982)	3.182 (1.196)	3.295 (1.069)	3.500 (1.065)	3.051 (1.191)	3.282 (1.297)
Q10C	3.025 (1.310)	3.478 (1.188)	3.271 (1.216)	3.605 (1.198)	3.375 (1.564)	3.341 (1.275)	3.571 (1.382)	3.128 (1.418)	3.359 (1.564)
Q11	2.725 (0.751)	2.728 (0.853)	2.724 (0.791)	2.895 (0.868)	2.919 (1.048)	2.614 (0.970)	2.875 (0.889)	2.454 (0.738)	2.737 (0.965)
Q12A	2.925 (0.944)	3.087 (1.029)	3.229 (0.905)	3.233 (0.996)	3.125 (0.966)	2.955 (0.987)	3.167 (0.853)	2.846 (1.288)	3.077 (0.984)
Q12B	3.150 (1.051)	3.022 (1.085)	3.271 (0.962)	3.140 (1.104)	3.304 (1.264)	3.068 (1.169)	3.310 (0.897)	2.718 (1.234)	3.282 (1.146)
Q12C	3.200 (1.305)	2.978 (1.374)	3.396 (1.317)	3.023 (1.389)	3.855 (1.385)	3.000 (1.555)	3.571 (1.151)	2.744 (1.551)	3.128 (1.361)
Q13	2.150 (0.483)	2.304 (0.465)	2.229 (0.515)	2.402 (0.491)	2.300 (0.564)	2.364 (0.532)	2.357 (0.618)	2.205 (0.695)	2.128 (0.615)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
Q14A	1.975 (0.158)	1.935 (0.250)	1.917 (0.279)	1.930 (0.258)	1.875 (0.335)	1.932 (0.255)	1.905 (0.297)	1.897 (0.307)	1.974 (0.160)
Q14B	1.950 (0.221)	2.000 (0.000)	1.979 (0.144)	2.000 (0.000)	1.875 (0.335)	2.000 (0.000)	1.929 (0.261)	1.949 (0.223)	1.949 (0.223)
Q14C	1.825 (0.385)	1.674 (0.474)	1.708 (0.459)	1.791 (0.412)	1.700 (0.464)	1.727 (0.451)	1.786 (0.415)	1.795 (0.409)	1.718 (0.456)
Q14D	1.975 (0.158)	1.804 (0.401)	1.875 (0.334)	1.837 (0.374)	1.875 (0.335)	1.841 (0.370)	1.833 (0.377)	1.846 (0.366)	1.846 (0.366)
Q14E	1.975 (0.158)	1.935 (0.250)	1.938 (0.245)	1.930 (0.258)	1.925 (0.267)	1.955 (0.211)	1.905 (0.297)	1.949 (0.223)	1.949 (0.223)
Q14F	1.525 (0.506)	1.413 (0.498)	1.479 (0.505)	1.535 (0.505)	1.425 (0.501)	1.318 (0.471)	1.333 (0.477)	1.436 (0.502)	1.436 (0.502)
Q14G	1.750 (0.439)	1.717 (0.455)	1.875 (0.334)	1.767 (0.427)	1.825 (0.385)	1.659 (0.479)	1.714 (0.457)	1.795 (0.409)	1.744 (0.442)
Q14H	1.850 (0.362)	1.870 (0.341)	1.771 (0.425)	1.860 (0.351)	1.825 (0.385)	1.707 (0.461)	1.881 (0.328)	1.872 (0.339)	1.872 (0.339)
Q34A	2.125 (1.202)	2.609 (1.308)	2.229 (1.356)	2.581 (1.367)	2.562 (1.582)	2.818 (1.483)	2.381 (1.413)	2.590 (1.534)	2.231 (1.441)
Q34B	1.850 (1.145)	1.870 (1.240)	2.125 (1.393)	2.465 (1.420)	2.650 (1.703)	1.977 (1.248)	2.147 (1.354)	2.385 (1.480)	2.051 (1.356)
Q34C	3.075 (1.248)	3.087 (1.347)	3.146 (1.337)	3.140 (1.302)	3.182 (1.447)	3.318 (1.377)	3.262 (1.170)	3.205 (1.454)	2.821 (1.254)
Q34D	2.875 (1.399)	3.022 (1.468)	2.875 (1.525)	2.837 (1.463)	3.248 (1.256)	2.795 (1.472)	3.167 (1.286)	2.844 (1.348)	2.718 (1.376)
Q34E	1.500 (1.013)	1.457 (0.912)	1.646 (1.041)	2.140 (1.457)	1.941 (1.340)	1.477 (0.927)	1.667 (1.097)	1.667 (1.177)	1.436 (0.968)
Q34F	1.875 (0.966)	2.304 (1.348)	2.063 (1.295)	1.954 (1.090)	2.050 (1.197)	1.841 (1.098)	1.833 (0.935)	2.026 (1.367)	2.051 (1.395)
Q34G	1.425 (0.747)	1.326 (0.790)	1.479 (0.899)	1.512 (0.910)	2.075 (1.347)	1.455 (1.130)	1.476 (0.994)	1.667 (1.264)	1.872 (1.380)
Q34H	1.700 (0.966)	1.565 (1.068)	1.521 (0.899)	2.047 (1.362)	2.144 (1.389)	1.455 (0.901)	1.643 (1.226)	1.692 (1.173)	2.077 (1.403)
Q34I	1.300 (0.687)	1.283 (0.779)	1.583 (1.069)	1.907 (1.324)	1.982 (1.303)	1.682 (1.137)	1.500 (0.994)	1.590 (0.993)	1.949 (1.468)
Q34J	2.050 (1.280)	2.217 (1.413)	2.250 (1.345)	2.395 (1.400)	2.734 (1.566)	1.977 (1.285)	2.452 (1.418)	2.667 (1.420)	2.564 (1.667)
Q34K	2.775 (1.405)	2.370 (1.420)	2.542 (1.487)	2.953 (1.558)	2.690 (1.417)	2.386 (1.543)	2.119 (1.253)	2.436 (1.465)	3.103 (1.429)
Q35	1.765 (0.781)	1.826 (0.643)	1.788 (0.600)	1.857 (0.648)	1.933 (0.828)	1.762 (0.617)	2.024 (0.724)	2.000 (1.000)	2.156 (0.954)
Q36	51.538 (35.743)	51.250 (25.495)	40.811 (27.016)	45.294 (32.682)	42.593 (36.331)	42.069 (31.666)	46.471 (33.744)	47.917 (35.750)	38.667 (35.011)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
Q37A	2.190 (1.213)	2.630 (1.123)	2.448 (1.068)	2.465 (1.316)	3.025 (1.310)	2.444 (1.335)	2.976 (1.278)	2.321 (1.127)	2.220 (1.337)
Q37B	3.710 (1.083)	3.957 (1.010)	3.871 (1.104)	3.628 (1.215)	3.820 (0.957)	3.882 (1.146)	3.952 (1.188)	3.867 (1.239)	3.524 (1.388)
Q37C	3.604 (0.973)	4.065 (0.929)	3.827 (0.953)	3.605 (1.256)	3.643 (1.143)	3.403 (1.242)	3.833 (1.188)	3.736 (1.271)	3.670 (1.192)
Q37D	3.270 (1.147)	3.196 (1.276)	3.152 (1.130)	3.186 (1.314)	3.607 (1.314)	2.961 (1.447)	3.571 (1.233)	3.161 (1.225)	3.406 (1.244)
Q37E	3.548 (1.211)	3.478 (1.295)	3.534 (1.218)	3.558 (1.201)	3.791 (1.224)	3.742 (1.143)	3.571 (1.328)	3.786 (1.454)	3.793 (1.393)
Q38	3.850 (0.736)	3.913 (0.784)	3.958 (0.798)	3.698 (1.103)	3.947 (0.932)	3.886 (0.689)	3.714 (0.918)	3.872 (1.151)	4.000 (0.889)
Q39	3.800 (0.648)	3.826 (0.570)	3.833 (0.753)	3.442 (1.098)	3.650 (0.949)	3.659 (1.077)	3.524 (0.890)	3.436 (1.314)	3.667 (1.009)
H1	23.738 (21.136)	20.717 (17.119)	24.833 (16.953)	23.977 (19.109)	12.575 (11.589)	18.511 (16.973)	20.048 (17.024)	17.641 (15.895)	14.769 (12.907)
H2	1.400 (0.496)	1.304 (0.465)	1.375 (0.489)	1.488 (0.506)	1.500 (0.506)	1.432 (0.501)	1.476 (0.505)	1.359 (0.486)	1.590 (0.498)
H3	3.150 (1.657)	2.543 (1.425)	2.521 (1.271)	2.512 (1.298)	3.075 (2.043)	2.864 (1.679)	2.714 (1.715)	2.718 (1.376)	2.564 (1.483)
H4_1	0.500 (0.506)	0.478 (0.505)	0.604 (0.494)	0.442 (0.502)	0.475 (0.506)	0.477 (0.505)	0.548 (0.504)	0.462 (0.505)	0.615 (0.493)
H4_2	0.175 (0.385)	0.130 (0.341)	0.146 (0.357)	0.279 (0.454)	0.125 (0.335)	0.250 (0.438)	0.167 (0.377)	0.179 (0.389)	0.179 (0.389)
H4_3	0.225 (0.423)	0.239 (0.431)	0.208 (0.410)	0.163 (0.374)	0.075 (0.267)	0.045 (0.211)	0.143 (0.354)	0.128 (0.339)	0.051 (0.223)
H4_4	0.125 (0.335)	0.196 (0.401)	0.063 (0.245)	0.093 (0.294)	0.050 (0.221)	0.045 (0.211)	0.095 (0.297)	0.154 (0.366)	0.026 (0.160)
H4_5	0.075 (0.267)	0.087 (0.285)	0.083 (0.279)	0.070 (0.258)	0.175 (0.385)	0.250 (0.438)	0.048 (0.216)	0.103 (0.307)	0.154 (0.366)
H4_6	0.050 (0.221)	0.022 (0.147)	0.000 (0.000)	0.116 (0.324)	0.200 (0.405)	0.068 (0.255)	0.095 (0.297)	0.179 (0.389)	0.077 (0.270)
H5	17.980 (27.098)	19.130 (27.066)	14.896 (24.178)	17.674 (24.087)	21.000 (27.531)	20.227 (25.924)	22.381 (30.827)	20.513 (30.258)	19.744 (22.997)
H6	8.171 (8.991)	8.935 (11.324)	9.813 (11.490)	12.349 (17.651)	15.075 (16.275)	22.216 (77.420)	13.571 (15.137)	12.000 (14.325)	13.718 (18.114)
H7	51.500 (18.194)	46.739 (19.895)	45.208 (20.730)	41.860 (19.549)	51.750 (23.412)	46.842 (16.567)	44.643 (19.643)	38.333 (17.930)	47.692 (24.002)
H8	10.950 (12.718)	10.913 (12.561)	9.792 1(1.132)	9.365 (9.063)	11.525 (23.629)	5.193 (5.308)	10.119 (13.916)	8.846 (8.704)	10.821 (16.735)
H9	6.325 (3.518)	4.804 (2.786)	5.938 (3.297)	6.116 (2.954)	5.200 (3.596)	5.364 (2.981)	4.333 (2.656)	4.256 (2.562)	5.921 (3.459)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
O1	4.300 (0.723)	4.217 (0.892)	4.191 (0.851)	4.070 (0.936)	4.154 (0.933)	4.227 (0.803)	4.286 (0.944)	4.026 (1.135)	3.949 (1.146)
O2	2.300 (0.758)	2.435 (0.620)	2.128 (0.769)	2.209 (0.638)	1.923 (0.623)	2.250 (0.686)	2.244 (0.799)	2.128 (0.732)	1.974 (0.668)
O3A	3.925 (0.997)	4.065 (0.998)	3.958 (1.110)	3.814 (1.097)	4.450 (1.061)	4.318 (1.006)	4.381 (1.011)	3.513 (1.275)	3.282 (1.356)
O3B	3.900 (1.128)	3.978 (1.022)	3.938 (1.040)	3.791 (1.081)	4.000 (1.301)	4.068 (0.974)	4.071 (0.947)	3.667 (1.364)	3.872 (1.380)
O3C	4.475 (0.751)	4.370 (0.928)	4.383 (0.922)	4.214 (1.001)	3.359 (1.646)	4.591 (0.816)	4.262 (1.127)	4.256 (1.141)	3.308 (1.454)
O3D	2.925 (1.228)	2.565 (0.981)	3.362 (1.169)	2.907 (1.211)	3.053 (1.413)	3.205 (1.133)	3.238 (1.165)	3.077 (1.201)	3.795 (1.080)
O3E	3.575 (1.130)	3.674 (1.012)	3.766 (1.088)	3.767 (1.043)	4.053 (1.251)	3.750 (1.059)	4.000 (1.082)	3.385 (1.350)	3.184 (1.392)
O3F	4.000 (1.352)	2.186 (1.484)	2.844 (1.745)	2.512 (1.832)	4.917 (0.368)	1.814 (1.452)	2.825 (1.838)	3.158 (1.763)	3.158 (1.838)
O3G	4.676 (0.747)	4.087 (1.330)	4.609 (0.745)	4.429 (1.016)	4.541 (1.095)	4.651 (0.720)	4.902 (0.374)	3.342 (1.744)	2.974 (1.896)
O3H	4.103 (0.788)	3.978 (1.125)	4.239 (0.923)	3.857 (1.181)	4.135 (1.206)	4.000 (1.078)	4.366 (0.829)	4.079 (1.217)	3.079 (1.566)
O3I	3.975 (1.121)	4.043 (1.246)	3.261 (1.324)	3.619 (1.287)	3.886 (1.451)	2.636 (1.348)	3.881 (1.214)	3.658 (1.361)	4.179 (1.167)
O3J	3.744 (1.312)	3.543 (1.456)	3.413 (1.257)	3.537 (1.451)	4.417 (1.105)	3.045 (1.257)	4.000 (1.118)	3.784 (1.475)	3.472 (1.682)
O3K	4.750 (0.707)	4.422 (0.892)	4.638 (0.705)	4.524 (0.773)	2.541 (1.835)	4.636 (0.650)	4.488 (0.898)	4.568 (0.867)	2.684 (1.832)
O3L	4.250 (0.927)	4.435 (0.935)	4.085 (1.018)	4.333 (0.928)	3.222 (1.570)	3.955 (0.987)	4.244 (0.969)	3.757 (1.342)	2.842 (1.603)
O3M	3.590 (1.332)	3.087 (1.092)	3.261 (1.405)	3.429 (1.172)	3.590 (1.428)	3.159 (1.275)	3.317 (1.234)	3.868 (1.189)	3.744 (1.292)
O3N	4.286 (1.496)	3.375 (1.598)	3.800 (1.789)	3.000 (2.309)	3.000 (2.000)	3.444 (1.878)	3.333 (1.581)	2.000 (0.000)	4.571 (0.787)
O4A	4.025 (0.768)	4.133 (0.588)	4.021 (0.675)	3.930 (0.828)	4.025 (0.862)	4.047 (0.575)	4.167 (0.621)	3.632 (0.751)	3.667 (0.816)
O4B	4.150 (0.802)	4.378 (0.614)	4.277 (0.649)	4.070 (0.768)	4.256 (0.993)	4.310 (0.715)	4.220 (0.652)	4.105 (0.689)	4.194 (0.786)
O4C	4.250 (0.809)	4.364 (0.574)	4.340 (0.600)	4.163 (0.785)	3.889 (1.369)	4.419 (0.698)	4.125 (0.757)	3.919 (0.954)	4.063 (0.840)
O4D	3.516 (0.926)	3.595 (0.865)	3.674 (0.732)	3.575 (0.712)	3.697 (1.045)	3.917 (0.806)	3.632 (0.786)	3.528 (0.910)	3.784 (0.854)
O4E	3.641 (0.811)	3.950 (0.783)	3.705 (0.795)	3.825 (0.813)	3.947 (1.064)	3.692 (0.863)	3.975 (0.800)	3.457 (0.852)	3.483 (0.911)

Table G-2
Summary Statistics
Means and Standard Deviations by City
Mean (SD) — First Row Shows n per City (cont.)

City	ALB	BIL	CMH	DEN	MIA	MSN	OKC	PDX	SAN
O4F	4.310 (0.891)	3.000 (1.600)	3.813 (1.148)	3.552 (1.213)	4.333 (0.737)	3.059 (1.638)	3.556 (1.450)	3.636 (1.255)	3.760 (1.300)
O4G	3.758 (0.969)	3.814 (0.958)	3.841 (0.834)	3.634 (0.915)	4.026 (0.932)	3.900 (0.841)	4.262 (0.828)	3.136 (1.320)	3.583 (1.176)
O4H	3.800 (0.901)	3.930 (0.737)	3.814 (0.732)	3.615 (0.935)	3.868 (1.070)	3.971 (0.785)	3.829 (0.972)	3.686 (0.900)	3.519 (1.014)
O4I	3.970 (0.883)	4.356 (0.743)	3.765 (0.819)	3.902 (0.768)	4.029 (0.969)	3.742 (0.930)	3.725 (0.933)	3.971 (0.822)	3.857 (1.004)
O4J	4.162 (0.834)	3.588 (0.988)	3.727 (0.845)	3.487 (0.914)	3.892 (1.100)	3.686 (0.993)	3.513 (0.970)	3.148 (1.134)	3.708 (0.859)
O4K	4.050 (0.846)	4.024 (0.570)	3.813 (0.790)	3.814 (0.824)	3.111 (1.649)	4.070 (0.828)	3.868 (0.844)	3.811 (0.739)	3.750 (0.944)
O4L	3.657 (0.906)	3.864 (0.668)	3.543 (0.780)	3.488 (0.910)	3.438 (1.366)	3.622 (0.893)	3.625 (1.030)	3.353 (0.950)	3.214 (1.197)
O4M	3.786 (0.833)	3.429 (0.959)	3.526 (0.979)	3.750 (0.899)	3.438 (1.366)	3.720 (0.843)	3.622 (0.924)	3.844 (0.847)	3.912 (0.965)
O4N	4.167 (1.169)	3.500 (0.577)	3.800 (0.837)	4.000 (0.000)	3.600 (1.673)	3.800 (1.304)	4.000 (0.632)	4.000 (0.816)	3.000 (0.894)
O5A	6.050 (5.914)	6.717 (6.914)	5.583 (6.384)	4.452 (3.070)	5.135 (6.985)	4.634 (3.923)	4.262 (4.849)	8.718 (8.179)	10.270 (8.569)
O5B	4.091 (0.971)	6.929 (6.933)	4.550 (1.731)	5.765 (4.024)	10.800 (8.967)	4.900 (3.553)	4.100 (3.985)	6.400 (6.377)	13.000 (11.158)